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Integrated assessment of sustainability trade-offs and pathways for global bioenergy production: Framing a novel hybrid approach

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ABSTRACT

Current controversies and debates on bioenergy production in the areas of greenhouse gases emission reduction, food and energy security, social exclusion and welfare erosion, and ecosystem deterioration attest to the challenges which the bioenergy sector has to overcome to achieve its global production potentials. Because it is yet an evolving sector, the sustainability of bioenergy production in different regions is very elusive. Experiences show that bioenergy policies in one region can have impacts not only on its own but also on other regions' social, economic and ecological sustainability. It is thus important to assess development pathways for bioenergy to exploit the potential benefits and forestall any unnecessary costs. This paper frames a novel hybrid approach for assessing bioenergy potentials for regions with diverging economic, social and ecological systems. The approach is based on a conceptual framework that takes into account trade-offs decisions on sustainability goals and production options in the assessment of bioenergy pathways. It combines different empirical techniques for the systematic investigation of trade-offs and pathways including fuzzy logic, conjoint, logit, and path analyses. To show the relevance and utility of these techniques for the integrated assessment of trade-offs and pathways in bioenergy development, we illustrated their application using results and data from previous related studies.

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1. Introduction

Bioenergy is a growing sector where desired pathways[1] of development are highly contested in science and policy alike because of its potential paradoxical impacts on the different sectors of the economy and population, particularly if its development is not appropriate to the existing social, economic and ecological systems. On the positive end, reduction in green house gases (GHG) emissions, increase in energy security, promotion of rural development, and increase in export revenues are the most cited arguments for bioenergy production. However, there are as yet few actual data to support these assertions because bioenergy is still a young and developing sector. Most studies on bioenergy potentials and impacts are largely based on concepts and/or scenarios remote from the real complexity of the global system (e.g. [1–4]). The current debates on the relationships between bioenergy crops and GHG emissions [5–7] and bioenergy development and rural development [8–10] attest to the uncertainties in the future development of bioenergy. Assessing the potentials of bioenergy production is not straightforward because "[b]io-energy is quite an [atypical] energy supply option due to its diversity and inter-linkages with many other technological (thermo-chemical conversion options, biotechnology, agronomic, etc.) and policy areas (climate, energy, agriculture and waste policy)" [11, p. 323]. The institutional structure of bioenergy is complex because it involves different products, different sectors and a range of actors interacting at and across different levels [8], thus it not only provides opportunities to generate multiple benefits apart from energy generation, but also causes conflict with many interests due to all those inter-linkages [11]. Hence, on the negative end, the recent undesirable experiences, among others, on food availability and accessibility (e.g. [12–14]), forest degradation (e.g. [15–18]), and social conflicts (e.g. [2,19–21]) attest to these complex relationships, which early policies promoting bioenergy have overlooked. Cognisant of the negative impacts of one region's bioenergy policies not only on its own but potentially also on other regions' social, economic and ecological systems, a sustainable development in global bioenergy production is deemed necessary to exploit the potential benefits and forestall any unnecessary costs, and to ensure equal distribution of benefits and costs among regions, particularly between developed and developing regions and, more importantly, between rich and poor communities in these regions. Although various definitions exist to understand sustainable development [22–26], the concept of sustainability is widely accepted as having three dimensions or pillars – economic, social and ecological (or environmental). However, there are disagreements on how to appropriately frame these pillars in evaluating or estimating sustainability. A large number of approaches are used to measure sustainable development and the choice of approaches usually depends on the context and scale of analysis. In the bioenergy context, we propose to focus sustainability assessments on trade-offs and pathways in view of the following challenges in the bioenergy sector:

- Competing land use between food and fuel production, and between first and second generation bioenergy products;
- Finding optimal scale of production (i.e. local versus commercial scale) to promote rural development;
- Creating a balance between domestically produced and imported biomass products and their feedstocks;
- Competing conversion technologies due to diverse range of options available to use and develop bioenergy; and
- Diverging strategies in pursuit of bioenergy sustainability due to contextual differences across countries.

Trade-off analysis is used in various fields as a concept to frame knowledge discords and a tool to analyse alternative options, for example, in industrial research to assess transport decisions and product manufacturing [27,28], in health research to compare the benefits and costs of different medical interventions [29,30], in agriculture research to investigate agriculture and farming systems [31,32], etc. In sustainability science, many concepts and tools explaining its theoretical basis were derived from the fields of economics, particularly welfare, development, environmental and ecological economics [26]. The approaches for assessing sustainability are criticised for focusing on balancing the trade-offs and thus highlighting the competing interests and potential conflicts between the different sustainability pillars. Gibson [25] argues that the sustainability concept emphasises interconnections and interdependencies, hence it is about integrating and avoiding trade-offs to the extent possible. However, Gasparatos et al. [26] explain the need for sustainability integrated assessment that goes beyond simply integrating the different pillars of sustainability. They suggest that future research should consider the adoption of a combination of biophysical and socio-economic tools to achieve a more comprehensive sustainability perspective, which is in the spirit of the "hybrid type of sustainability assessment". Referring to the study of Gibson et al. [33] and Gibson [25], they explain that behind this hybrid approach is the conscious attempt to discourage trade-offs to the greatest extent possible.

More importantly, however, we take on the challenge of integrating the outputs from such a pluralistic approach because we believe that it as an essential process for identifying not only inevitable trade-offs, but also alternative pathways for a sustainable bioenergy production. Mapping out an actual pathway is even more challenging than defining sustainable development [34]. Kaditi [35] concludes that it is increasingly urgent to map a pathway for the global bioenergy sector that supports sustainable development due to the possibility of bioenergy to provide a solution to one specific problem whilst simultaneously creating several other problems. This paper is thus guided by the hypothesis that trade-off decisions on achieving a balance among social, economic and ecological goals are necessary conditions for assessing development pathways in bioenergy. We aim to contribute to the research efforts on sustainability integrated assessment by proposing a new hybrid approach that will allow for the systematic investigation of the sustainability of bioenergy production in selected regions of the world with particular focus on identifying trade-offs and pathways. The next section (Section 2) presents the thematic and schematic framework for this hybrid approach, which we refer to as STRAP (sustainability trade-offs and pathways). Section 3 presents the sustainability concept for bioenergy. It discusses the most relevant

[1] Paths and pathways are used interchangeably in bioenergy literature. For consistency, we use in this paper the term paths to refer to the method of path analysis and pathways to refer to the outcome of the analysis.

determinants for a sustainable bioenergy production and the inter-linkages among them that could ensue sustainability trade-offs. Section 4 describes the complementary techniques for generating trade-off parameters and Section 5 presents how bioenergy pathways can be assessed using these parameters. Using data and results from other studies, Section 6 illustrates the utility of these techniques for assessing trade-offs and pathways. Finally, conclusions are presented in Section 7.

2. The STRAP approach

Fig. 1 presents the thematic and schematic framework of the hybrid approach STRAP. The framework summarises what are the data requirements for, the technical applications in, and knowledge generation from the STRAP approach, and how they link to one another in assessing trade-offs and pathways in bioenergy production. Although we aim to assess both, the ultimate objective of the STRAP approach is to identify bioenergy pathways using the estimated parameters from the trade-off analyses. In this paper, a pathway defines the probability of converting land use for bioenergy production as a function of the interrelationships between the social, economic and ecological pillars of sustainability. To clarify this definition, we group the framework into four themes (i.e. sustainability concept, trade-off parameters, data, and bioenergy pathways) and explain step-by-step how each theme is dealt with in the STRAP approach. Details of these themes are discussed in the next sections, but below are brief descriptions.

2.1. Sustainability concept

In any modelling approach, a concept defines the groundwork for the analysis and provides guidelines for the selection of the data. Following the three-pillar concept of sustainability, we define sustainability of bioenergy production based on a region's capacity to achieve a balance between economic stability, social equity and resource productivity (Fig. 1). Because the bioenergy sector is still in its development stage, there is as yet no universal concept to define the interconnections and interdependencies among these sustainability pillars. To identify these interconnections and interdependencies, we carried out a comprehensive literature review and established the most relevant determinants and indicators for each sustainability pillar. Determinants are factors or issues which significantly influence the nature of sustainability. Whenever possible, we chose the determinants on the basis of available theories (i.e. economic comparative advantage, strategic niche management, techno-economic paradigm, economic development). Moreover, the determinants not only represent the complementary and/or competitive views on the use of 1st and 2nd generation bioenergy crops for food and energy production, but also capture the inherent contradictions and controversies in achieving a balance between the three pillars of sustainability. Energy security, technology diffusion and market organisation are the determinants for economic stability; food security, welfare contribution and social exclusion for social equity; and feedstock options, resource capacity and land management for resource productivity (Fig. 1). Because they are abstract representation of ideas or concerns on bioenergy sustainability, we need indicators to provide concrete information or measurable facts on the state or level of these determinants. We based the selection of the indicators from the evidences in relevant case studies for different countries. The concept combines both quantitative and qualitative indicators. The latter is particularly important because many social and ecological indicators are hardly quantifiable. The sustainability concept is core to the STRAP approach because it supports the selection of indicators (or data) that feed into the trade-off assessments, which then generate the required parameters for the pathways. In particular, the information from the concept will be used for constructing inference rules for the fuzzy logic (Section 2.2) and identifying the pathway components for the path analysis (Section 2.3). Details on the nature and relevance of these indicators are presented in Section 3.

2.2. Trade-off parameters and data

Parameters are numerical values that define the system or set the conditions of its operation [36], and are usually used as inputs to model analysis. Following the pathway definition above (see Section 2), we require two types of parameters to set the logical conditions for the bioenergy pathways – first, the sustainability pillars trade-off and second, the production activities trade-off (Fig. 1). The trade-off parameters for the determinants of sustainability pillars are indices with values ranging from 0 to 1. They could be generated using fuzzy logic analysis. Fuzzy logic is a useful technique for combining quantitative and qualitative indicators, and for including policy preferences for these indicators. The inputs for the fuzzy logic analysis are time-series data of the indicators and their respective preference weights. The preferences are weights given to each indicator with values ranging from 0 to 100 percent. The weights could be estimated using conjoint analysis. The inputs for the conjoint are survey data from relevant stakeholders (e.g. policy-makers, scientists, bioenergy producers). The trade-off parameters for the production activities are probabilities of land use conversion into bioenergy production. The probabilities with values ranging from 0 to 100 percent could be estimated using spatiotemporal logit analysis. The dependent variables for the logit analysis are the presence or absence of land use change (or conversion). Land use changes reflect the social, economic and ecological needs of a changing society and are often driven by policies that intend to support these needs. Since the 1970s, for example, large expansion in agricultural land has been observed due to policies (e.g. green revolution, global trade) aiming to provide sufficient food supply to the rapidly growing population (Fig. 2). The increasing policy concern to protect the environment in the 1990s led to reforestation and forest protection in many countries. More recently, policies promoting the use of biomass for energy among others to enhance energy security and climate mitigation have resulted in the conversion of not only agricultural crops but also agriculture and forest areas into bioenergy production. These examples illustrate that land use changes are largely influenced by human activities. Taking this into account, the independent variables for the logit analysis are those variables representing not only biophysical features (e.g. soil, topography, erosion) of a geographical area but also the sustainability goals of a society. The former are spatial data from GIS maps and the latter are parameters of sustainability trade-offs generated from fuzzy logic analysis. Details on the techniques to parameterise time-series, spatial and survey data including fuzzy logic, conjoint and logit analyses are discussed in Section 4.

2.3. Bioenergy pathways

In layman's words, a pathway (or path) is defined as a course of action or way of achieving something [36], or a set of actions, especially ones which lead to a goal or result [37]. In the context of bioenergy, the course or set of actions are represented by the trade-off decisions on sustainability pillars and the goal or result is achieving bioenergy potentials. The higher the probabilities of land use conversion into bioenergy production, the higher are the bioenergy potentials. A bioenergy pathway thus measures the extent to which the potentials for bioenergy production can be realised in a particular country based on the trade-off decisions on social, economic and ecological goals of the society. In the STRAP approach, bioenergy pathways are diagrams showing the

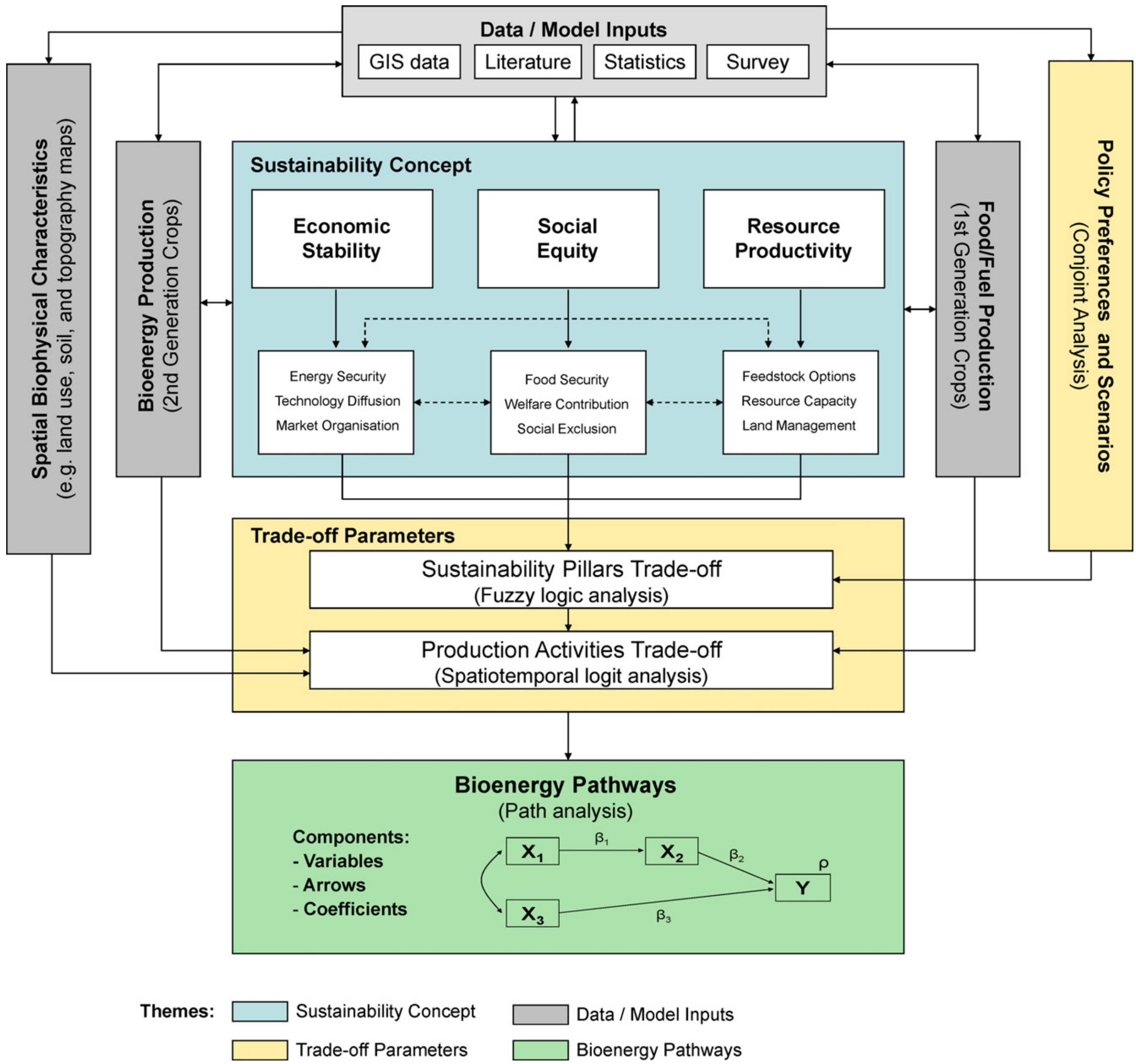

Fig. 1. Thematic and schematic diagram of the hybrid approach STRAP.

interconnections and interdependencies of the relevant (i.e. statistically significant) determinants of sustainability and their effects on the probabilities of land use conversion into bioenergy production (Fig. 1). The diagrams have three components: (1) the variables, representing the statistically relevant determinants; (2) arrows, showing the direction of relationships between these variables; and (3) coefficients, showing the magnitude of influence of these relationships to the probabilities of land use conversion. It is important to emphasise at this point that the bioenergy pathways in the STRAP approach are different from those in existing bioenergy literature describing the technical pathways for various bioenergy feedstocks (e.g. [11,38–40]). Because these diagrams are based on the logical analysis of the trade-offs among economic, social and ecological determinants of sustainability, here bioenergy pathways are a logical, not a technical analysis. Based on the trade-off parameters of sustainability pillars and production activities, the components of the bioenergy pathways including variables (i.e. X_i), arrows, and coefficients (i.e. β_i) could be generated using path analysis (Fig. 1). Details on this technique are presented in Section 5.

3. Sustainability concept for bioenergy

Table 1 presents the most relevant indicators for the determinants of sustainable bioenergy production which were identified through a comprehensive literature review. We describe in this section the conceptual interconnections and interdependencies between the determinants and their underlying indicators, which need to be taken into account in the assessments of sustainability trade-offs and pathways. Whenever necessary, we provide empirical support for the given arguments.

3.1. Economic stability

Energy is central to stable economic growth. Public concerns on energy security are due to short-term volatile prices and long-term supply of fossil fuels, particularly oil, which can destabilise the economy. The most important indicators of energy security include energy consumption, production and trade balance (Table 1). Clancy [8] explains that high oil price is linked to political insta-

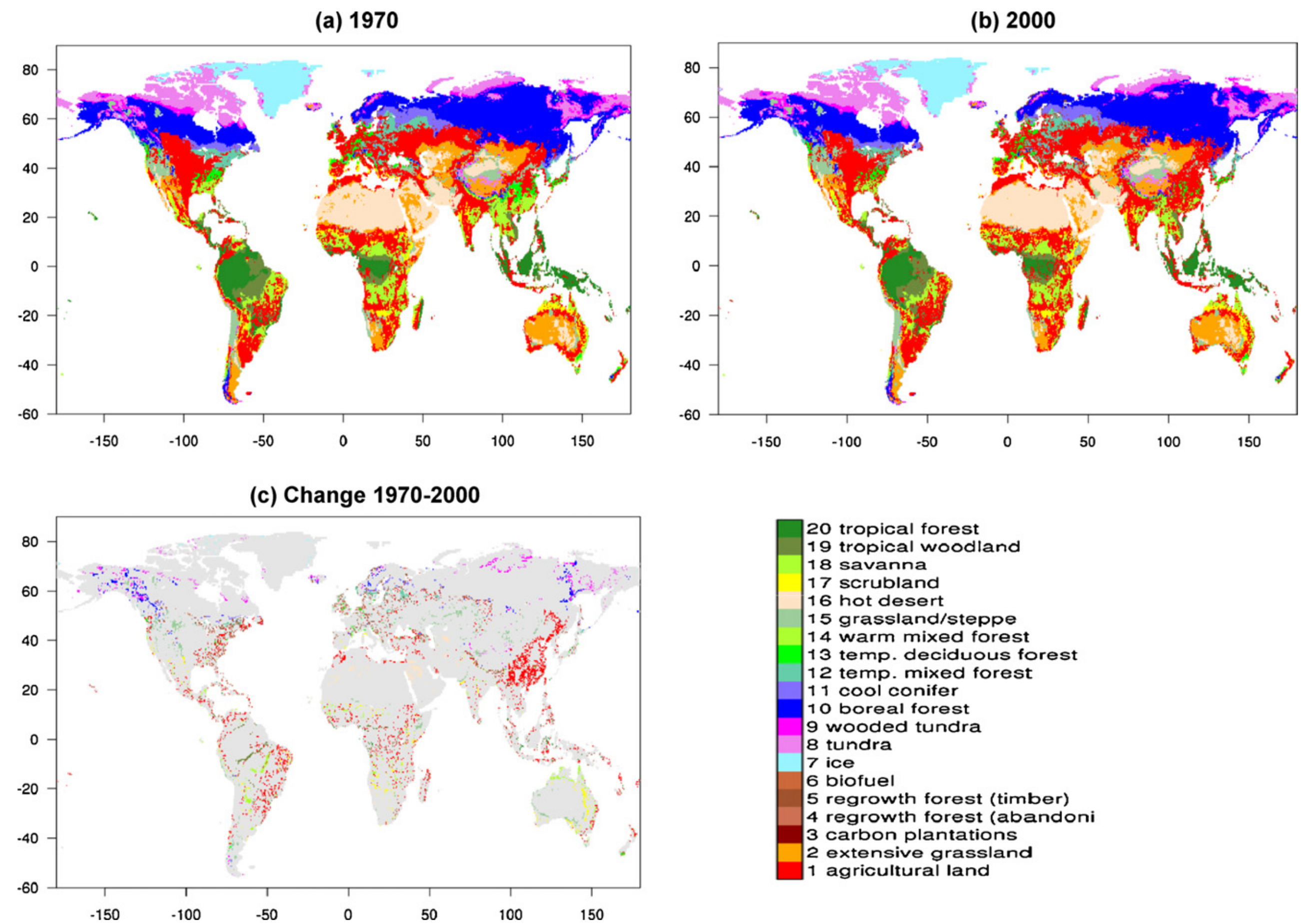

Fig. 2. Presence of land use change (c) from year 1970 (a) to year 2000 (b).
Data Source: IMAGE team, RIVM CD-ROM Publ. 481508018, Natl. Inst. for Public Health and the Environ., Bilthoven, Netherlands; 2001.

bilities that threaten energy supply security. The idea of reducing dependence on foreign sources of energy through local bioenergy production has thus increased the political popularity of biofuels [1,41,19], resulting in generous government targets for substituting biofuels for fossil fuels in the transport sector (e.g. 10 percent obligatory renewable energy share by 2020 in the EU; 5 percent biodiesel use by 2013 in Brazil; 20 percent reduction in petrol-based vehicles by 2020 in the US). Countries with little land endowments and high costs of biomass production will not reach their substitution goals without bioenergy trade [35,42,43]. The ability to substitute imported fossil fuel with domestic biofuel depends not only on the available land but also on the available conversion technologies. The diffusion of technologies is thus an important determinant of bioenergy development, with R&D investment and deployment as well as energy efficiency of these technologies as the most relevant indicators (Table 1). Research and development (R&D) investment makes innovative technologies available and technology deployment through pilot and demonstration projects makes them accessible to the public. However, the technical and cost (or techno-economic) efficiencies of these technologies ultimately influence the diffusion of bioenergy in the market [44]. Whilst current supply of bioenergy is largely produced from agricultural crops, the technology for producing ethanol from lingo-cellulose feedstock is expected to be commercially mature from year 2020 [45]. Mayfield et al. [46] argue that significant gains in the areas of research, development and education alone will not guarantee success in biomass industry. There is a need for a market outlet to utilize the product. Several studies suggest that the economic potential of bioenergy will depend on the development of market for the production and processing of biomass, and on overcoming the barriers to sustain its growth [11,46–50]. Ewing and Msangi [51] affirm the profitability of crop-based biofuels even for small farmers if the production, marketing, and distribution networks are designed appropriately. Handling, transportation and organisational structures can make technologies more feasible because of reduced supply uncertainty and thus cutting the costs [52,49]. Thus, the market for bioenergy needs to be organised to achieve its potentials. The most important indicators of market organisation include the development of market infrastructure, provision of market incentives, and elimination of trade constraints (Table 1).

Referring to the concept of strategic niche management, Rösch and Kaltschmitt [53] argue that, unlike other technologies where necessary infrastructure is established only after achieving a certain critical dissemination in the market, new bioenergy technologies cannot reach this required minimum diffusion without necessary infrastructure in place. Many studies suggest that policy incentives not only to promote technologies but also to develop market are thus necessary to make the biomass a competitive source of energy and support the growth of bioenergy market [46,48,53–57]. "The development of truly international markets for bio-energy may become an essential driver to develop [bioenergy] potentials, which are currently underutilised in many regions of the world" [50, p. 8]. So national policies supporting domestic bioenergy market should promote, not hinder the much needed expansion in international bioenergy trade. According to Heinimo and Junginger [58], the volume of foreign trade in bioenergy is at present insignif-

Table 1
Determinants and possible indicators of sustainability.

Sustainability pillars	Determinants	Indicators	Type and unit of indicators (i.e. data)
Economic stability	Energy security	(1) Energy consumption (2) Energy production (3) Energy trade balance	(1) Per capita energy consumption (2) (a) Percent GDP; (b) ratio small- versus large-scale companies (3) Ratio total energy import/export
	Technology diffusion	(1) R&D investment (2) R&D deployment (3) Energy efficiency	(1) (a) Type of policy incentives; (b) investment/GDP ratio (2) Pilot and demonstration projects: (a) type, (b) number (3) (a) Ratio energy to total biomass yield; (b) type of available technology
	Market organisation	(1) Market incentives (2) Market infrastructure (3) Trade constraints	(1) Investment subsidies: (a) type, (b) amount (2) Road and communication network: (a) type, (b) length (3) (a) Amount export and import tariffs; (b) type preferential trade agreement; (c) quality standards
Social equity	Food security	(1) Self-sufficiency (2) Purchasing power	(1) (a) Self-sufficiency ratio; (b) ratio food import/export (2) (a) Purchasing power parity; (b) per capita income
	Welfare contribution	(1) Sources of livelihood (2) Employment creation (3) Changes in lifestyle	(1) (a) Agriculture share in GDP; (b) bioenergy share in agriculture (2) (a) Percent employed in bioenergy activities; (b) scale of production facilities (3) (a) Type of energy use; (b) percent population with no access modern energy
	Social exclusion	(1) Property rights (2) People displacement	(1) Law and policy on land ownerships (2) (a) Number of affected people; (b) number of incidence of people displacement
Resource productivity	Feedstock options	(1) First generation (2) Second generation	(1) (a) Type of crops; (b) area planted to these crops (2) (a) Type of crops; (b) area planted to these crops
	Resource capacity	(1) Population pressure (2) Resource availability (3) Ecological sensitivity	(1) (a) Population density; (b) population growth (2) (a) Ratio potential/total land area; (b) ratio irrigated to total area (3) (a) Soil erosion/fertility index; (b) biodiversity level; (c) GHG reduction policy targets
	Land management	(1) Farm practices (2) Nature conservation	(1) Percent farmers engage in (a) multi-cropping practices, (b) organic farming, (c) rotation schemes, (d) erosion-reduction practices, etc. (2) Nature conservation (e.g. reforestation, diversification, protected areas): (a) type, (b) area

icant as compared to global production, except for wood pellets. International biomass and bioenergy market is expected to expand in the future,[2] but there are existing tariff and non-tariff barriers to exploiting trade potentials for both processed and unprocessed biomass energy sources. Bilateral or multilateral trade agreements among countries often provide some exemptions to these trade barriers, but there remain other barriers like international quality standards that cannot be easily resolved through preferential trade agreements. There are concerns that the cost of meeting these standards will reduce small farmers to growing only feedstock and lose the possibility to participate in the value-added component of the market chain [8]. Moreover, because bioenergy is relatively a young industry, it lacks standard and certification systems for global biomass trade that will control possible negative effects of large-scale biomass production and export like deforestation or the competition between food and fuel production [59]. Unless the growth in bioenergy market is achieved through sustainable production and trade, the development of the bioenergy sector is less likely to contribute to achieving social and ecological sustainability.

3.2. Social equity

The trade prospects created through bioenergy policies in developed countries made bioenergy as an appealing means of increasing foreign exchange revenues in developing countries. However, bioenergy trade in recent years had undesirable impacts on food security. The recent controversies on the impacts of bioenergy production on food availability and affordability made food security as one of the most urgent contemporary public issues on and, consequently, also one of the most important determinants of the sustainability of bioenergy production.[3] The levels of food self-sufficiency and purchasing power are some of the useful indicators of food security (Table 1). The drastic increase in prices of major food commodities in 2007 and 2008 caused food crisis resulting in protests and riots in many developing countries [3,14]. The conversion of agricultural crops and lands from food to bioenergy production has been claimed to contribute to short supply and thus high prices of major food commodities [8]. Estimates from a global commodity and trade model revealed an increase of 39 percent in maize prices, 21 percent in rice prices and 22 percent in wheat prices in 2006–2007 due to increased biofuel demand [3]. Rapid

[2] The reasons for this include: (a) lower prices of biomass in the developing countries with limited technologies and higher costs of bioenergy production in the developed countries with advanced technologies, (b) increase energy demand in fast growing economies like China and India, and (c) generous targets for substituting biofuels for fossil fuels to support energy security and climate policy.

[3] This is not surprising for several reasons [12,13]: (1) at risk are more than 800 million presently food-insecure people and an additional 2–2.5 billion people who could easily become food-insecure from rising commodity prices; (2) the current major bioenergy feedstocks including sugarcane, maize, cassava, palm oil, soy, and sorghum are the main sources of calorie among the food-insecure population; and (3) between 50 percent and 70 percent of the income are spent on food by urban and rural poor in many developing countries.

price increases in food commodities have considerable negative impacts on poverty reduction, which can undermine rural development in many developing countries. The contributions of the bioenergy sector to welfare through livelihood and employment generation are the most important indicators related to rural development (Table 1). Clancy [8] argues that whilst the Northern agenda strongly links bioenergy production among others to fuel security and environmental concerns, the ostensibly Southern agenda see it as a means to promote rural development. On the one hand, those in favour of bioenergy claim that bioenergy production could generate rural livelihood because [8,51,60]: (1) new demand for agricultural commodities other than traditional uses for food, feed and fibre are generated (i.e. diversification), which could also reduce the volatility of commodity prices; (2) feedstock could be processed close to the local source of production, thus income is retained in rural communities; (3) the economies of scale in bioenergy production would offer opportunity for community-based managed energy plantations, thus ensuring higher income even for smallholders; and (4) marginal and idle lands can be used for production of second generation feedstock (see discussion below), thus extending the land base for agricultural activities. On the other hand, others claim that bioenergy production could also create employment because ([61] as cited in [60]): (1) agricultural production in many developing countries is labour-intensive, thus large-scale plantations through local or foreign investments would increase demand for agricultural workers; and (2) construction and operation of bioenergy conversion facilities would generate additional economic activity requiring skilled workers.

Although there are few cases of success on livelihood generation (e.g. [62,63]), many remain sceptical of the role of bioenergy in welfare development due to many infrastructural [64], technological [51] and organisational [65] barriers. Agglomeration and investment of capital have the potential to increase the efficiency of production and produce employment in the rural sector but, if left unregulated, they could push rural dwellers and small farmholders off their land to pave way for commercial exploitation of biofuels [2,19,66]. Foreign and local investors have already started buying lands for growing bioenergy crops in Africa (e.g. [19]), Asia (e.g. [8,62]) and Brazil (e.g. [2]) resulting in displacement of poor rural people. In these regions, insecure land tenure or lack of clear property rights is causing dispossession of land among the poor [60,67]. "In many cases, lands perceived to be "idle", "under-utilised", "marginal" or "abandoned" by government and large private operators provide a vital basis for the livelihoods of poorer and vulnerable groups, including through crop farming, herding and gathering of wild products" ([68] as cited in [2, p. 23]). For these reasons, it is important to take into account social exclusion, which can be measured by the quality of property rights and quantity of people displaced, as an important determinant of sustainable bioenergy production (Table 1). Clancy [8] argues that, although reports on land conflicts is increasing with the increase in biofuel production, displacement of poor farmers is not an inherent characteristics of biofuels but is a consequence of political process vested in power relations in a particular context. Thus, if policies ensure social equity not only through generation of livelihood and employment but also through prevention of social exclusion, rural populations are stand to benefit more from technological innovation in the bioenergy sector. Improvement in lifestyle is another useful welfare contribution of modern bioenergy technologies (Table 1). Energy choices (i.e. type and amount) resemble lifestyle quality because energy consumption is (1) essential to the provision of basic needs (e.g. food, clean water, health, shelter, etc.) [69], (2) highly correlated to decreased working hours and improved standard of living [70,71], (3) a manifestation of women's role in the society (i.e. reduce household drudgery) [72,69], and (4) related to decisions on household comfort and local social cohesion [73]. Some studies suggest that the wider range of choices on available fuel and equipment distinguishes a better off household from a poor one and that the sources of energy are a function of household income [69,60].

3.3. Resource productivity

The sources of biomass feedstock, which can be categorised as first generation and second generation crops, are an important determinant of ecological sustainability of bioenergy production (Table 1). The widespread policy support for bioenergy R&D in the 1980s has promoted technologies to convert biomass from first generation crops; i.e., from sugar-rich crops (e.g. sugar cane, sugar beets) and starch-rich crops (e.g. maize, wheat, potato, cassava) into ethanol through fermentation and to convert vegetable oil (e.g. rapeseed, soybean) and palm oil (e.g. palm, coconut) into biodiesel through esterification. The global production of ethanol almost tripled from 20 to 50 billion litres and biodiesel increased from 0.8 to almost 4 billion litres from 2001 to 2007 [74]. The biomass feedstock for these biofuels and the associated conversion technologies are, however, not sustainable because they have negligible effect on GHG mitigation, reduce biodiversity, compete on land use for food production, and have high costs of production (see e.g. [39,40,75]). The high costs of bioenergy production particularly from dedicated energy crops are contributed by a number of factors including use of fertile and thus valuable agricultural land, intensive farm management requiring more labour, and low net energy yield per hectare of biomass [11,39]. A significant part of the global land area is already used for agriculture and most of the land use conversions between 1970 and 2000 were in favour of agriculture and related activities (Fig. 2). These conversions have environmental implications. According to Gomiero et al. [76], agriculture activities including improved pasture and co-adapted grassland account for about 40 percent of land surface and nearly 85 percent of annual global water withdrawals. The use of agricultural crops for bioenergy production will further strain both land and water resources, which are already under pressure from food, habitat and commercial needs of the rapidly growing population. The water footprint of biomass is 70–400 times larger than that from other energy sources (e.g. wind, solar, fossil) [77], thus ongoing increase in biofuel production could result in a significant increase in water demand and worsen local and regional water shortages [78,79]. The massive conversion of land into oil palm production particularly in Southeast Asia is threatening biodiversity because oil palm plantations support much fewer species than forests and other tree crops [15,80]. Moreover, conversion of rainforests, peatlands, savannas, or grasslands to produce biofuels from first generation bioenergy crops would release far more CO_2 than the annual GHG reductions that these biofuels would provide by displacing fossil fuels [5,6].

The foregoing discussion emphasises the relevance of determining the relationships of the feedstock options to the resource capacity, which most relevant indicators include resource availability (i.e. land, water), ecological sensitivity (i.e. soil quality, biodiversity and climate mitigation) and population pressure (i.e. density and growth) (Table 1). The new green techno-economic paradigm suggests the use of new sources of biomass feedstock and advanced energy conversion technologies not only to produce energy- and cost-efficient bioenergy, but also to contribute to popular social concerns like rural development, food security and environmental protection. "Second generation bioenergy" using feedstock from agriculture or forestry residues, fast-growing trees, perennial grasses, and algae offers a promising techno-economic solution for several reasons (see e.g. [39,40,47,75]): (a) larger energy yields per hectare due to broadness of the feedstock base, (b) lower production costs per hectare due to the use of marginal lands and less management, and (c) suited for annual harvest using, in

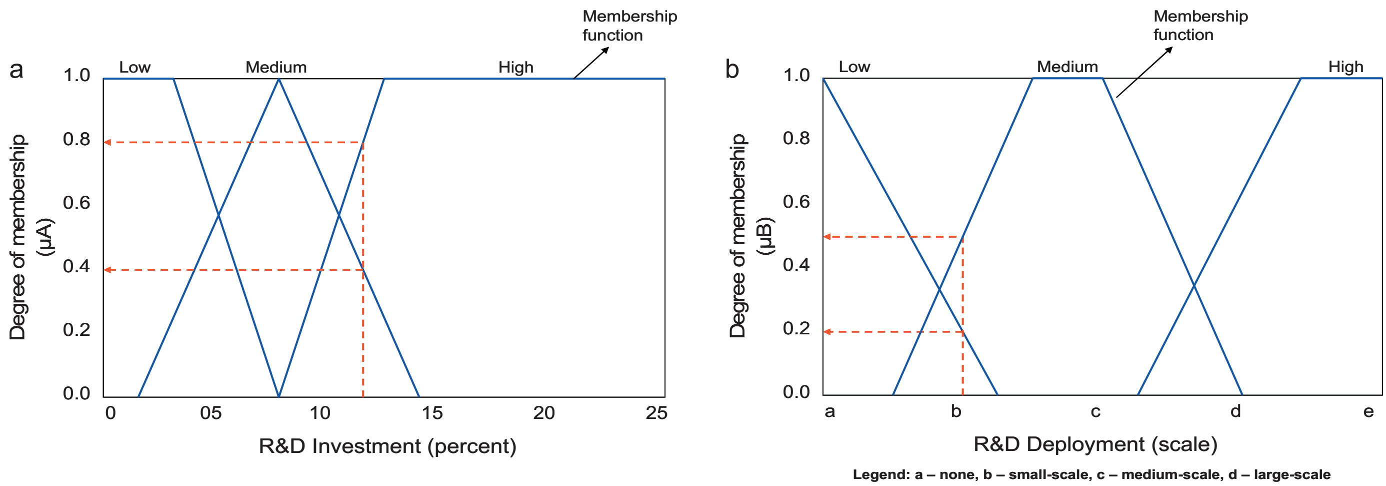

Fig. 3. Step 1 – fuzzification with membership function and degree of membership.

some cases, the same machineries as food crops. According to Londo et al. [47], a more sustainable energy economy for the future thus strongly depends on technologies that convert low-grade feedstock into high-value energy carriers. Although there are potentials to develop the technologies required to process second generation bioenergy feedstock, there are remaining environmental concerns that need attention. Using marginal or abandoned lands, which are frequently highly erodible, for producing and harvesting woody biomass plantations may be accompanied by increased soil erosion [81]. Removal of agricultural residues in the agro-system for use in bioenergy production could affect soil productivity due to soil fertility loss and soil erosion [76]. However, some authors suggest that many of the bioenergy production dilemmas could be solved through appropriate land use management, which main indicators include farm practices and nature conservation (Table 1). For example, Dale et al. [82] explain that perennial bioenergy crops should be considered a component of conservation farming systems to improve soil quality and reduce erosion. Plieninger and Bens [83, p. 273] argue that "the basic challenge for conservation is not biofuel use per se, but the way in which biomass is produced". Innovative land use systems are needed specifically designed for bioenergy that have high energy efficiency and support environmental conservation. Hennenberg et al. [84] indicate that although cultivation best practices vary widely depending on geography and feedstock, certain features are common including use of native species and local varieties, avoidance of monocultures, prioritization of perennial crops, adequate rotation schemes, low-erosion land-use methods (e.g. no-till systems), low input of agrochemical application and machinery, and minimal irrigation.

4. Parameterisation techniques

The foregoing discussions reveal that trade-off decisions among various social, economic and ecological determinants influence the sustainability of bioenergy production. This section discusses the relevant techniques for generating trade-off parameters of sustainability pillars and production activities from these determinants.

4.1. Fuzzy logic analysis

Fuzzy logic is a useful technique to generate trade-off parameters for the determinants of the sustainability pillars. Since the 1960s, fuzzy logic analysis is widely used to handle vagueness or inaccuracy in different fields including industrial control, military operations, economics, engineering, medicine, reliability analysis, and pattern recognition and classification [85]. More recently, it has also been applied in environmental science to analyse sustainability [86] and vulnerability [87,88]. Fuzzy logic has several advantages for modelling sustainability including its ability to combine quantitative and qualitative data, convert numerical data into linguistic values, include expert judgement and knowledge, represent non-linear relationships of interrelated data, make model assumptions transparent using inference rules, and generate multi-valued model outputs. The fuzzy logic analysis follows three steps, and each of these steps consists of two procedures:

(1) *Fuzzification:* (i) categorization of membership functions; and (ii) assessment of degree of memberships.
(2) *Fuzzy inference:* (i) construction of inference rules; and (ii) deduction of fuzzy estimates using these rules.
(3) *Defuzzification:* (i) transposition of fuzzy estimates; and (ii) aggregation of transposed fuzzy estimates.

In the first procedure of fuzzification, the numerical or verbal values of an indicator on the x-axis are categorised into comparable linguistic values using the membership function, whilst in the second procedure the given value of this indicator is translated into a scale (i.e. 0–1) using the degree of membership on the y-axis. Fig. 3a and b illustrates the fuzzification of the determinant "technology diffusion" using R&D investment (i.e. percent of GDP) and deployment (i.e. scale of pilot and demonstration projects) as indicators. Categorizing the data into "low", "medium" and "high", three membership functions corresponding to each of these linguistic values have to be constructed. The number of membership functions in the fuzzification diagram thus depends on the number of data categories. The shape of the membership functions defines the range of numerical values included for each linguistic value and the degree of membership μ of the selected data sample. In the fuzzification of R&D investment (Fig. 3a), for example, given an investment to GDP ratio of 12 percent, the membership functions for both categories medium and high are intersected, but not for category low. These intersections result in a membership value of 0.8 for the category high, 0.4 for the category medium, and 0.0 for the category low. The latter implies that R&D investment at 12 percent is definitely not low. In the fuzzification of R&D deployment (Fig. 3b), the scale of the bioenergy projects represents the qualitative data of this indicator. Assuming that most projects are small-scale bioenergy facilities, then the membership function for low category is intersected at a membership value of 0.2, for average cate-

1st Procedure	Inference rules between input indicators R&D investment (A) and deployment (B)		
rule 1:	If A is low and B is low	…	then C is low
rule 2:	If A is low and B is medium	…	then C is low
rule 3:	If A is low and B is high	…	then C is medium
rule 4:	If A is medium and B is low	…	then C is low
rule 5:	If A is medium and B is medium	…	then C is medium
rule 6:	If A is medium and B is high	…	then C is high
rule 7:	If A is high and B is low	…	then C is medium
rule 8:	If A is high and B is medium	…	then C is high
rule 9:	If A is high and B is high	…	then C is high
2nd Procedure	**Deducted degree of membership of the output index Technology diffusion (C)**		
rule 1:	μC(low) = min {0, 0.2}	…	μC(low) = 0
rule 2:	μC(low) = min {0, 0.5}	…	μC(low) = 0
rule 3:	μC(medium) = min {0, 0}	…	μC(medium) = 0
rule 4:	μC(low) = min {0.4, 0.2}	…	μC(low) = 0.2
rule 5:	μC(medium) = min {0.4, 0.5}	…	μC(medium) = 0.4
rule 6:	μC(high) = min {0.4, 0}	…	μC(high) = 0
rule 7:	μC(medium) = min {0.8, 0.2}	…	μC(medium) = 0.2
rule 8:	μC(high) = min {0.8, 0.5}	…	μC(high) = 0.5
rule 9:	μC(high) = min {0.8, 0}	…	μC(high) = 0

Note: Weight of indicator A is 70% and indicator B is 30%.

Fig. 4. Step 2 – fuzzy inference between input indicators and output index.

gory at 0.5, and for high category at 0. The latter implies that R&D deployment with small-scale projects is definitely not high. The degree of memberships generated for both R&D investment (poor = 0, middle-class = 0.4, rich = 0.8) and deployment (low = 0.2, average = 0.5, high = 0) are carried over to the second step of the fuzzy logic analysis.

In the first procedure of the fuzzy inference, the inference rules are constructed by defining the conceptual and/or logical relationship between the input indicators and the output index using linguistic "if-then" statements. The nature of the relationship will be based on the issues and concerns described in the sustainability concept in Section 3. To simplify the illustration, we now refer here to R&D investment as the input indicator A and R&D deployment as input indicator B to generate an index for technology diffusion. Assuming that the survey and consultations in the case study region informed that R&D investment (e.g. 70 percent) has more weight than the R&D deployment (e.g. 30 percent), then this information should be taken into account in constructing the inference rules (see Section 4.2 for the estimation of the weights). Looking at rule 2 in the upper half of Fig. 4, even if indicator B has "medium" category, index C remains "low" because indicator B, which has more weight than indicator A, has only "low" category. Similarly, in rule 8, index C turns "high" because the "medium" category of indicator B is combined with the "high" category of indicator A. In the second procedure of the fuzzy inference, the fuzzy estimates of technology diffusion (C) are deducted from the degree of membership of indicators A and B, which were computed from the first step of the fuzzy logic analysis. The logical connective "and" in the above inference rules means that mathematical relationship between indicators A and B is an intersection (see [86] for other logical connectives). In rule 1, for example, the mathematical expression for the intersection (A, B) is: $\mu C(\text{low}) = \min\{\mu A, \mu B\}$, where the minimum value of the degree of membership of indicators A and B is selected. Applying the degree of memberships of indicators A and B based on the constructed inference rules, the results of the deduction in fuzzy inference for the technology diffusion (C) are shown in the lower half of Fig. 4. The most relevant results are those with non-zero estimates including $\mu C(\text{low}) = 0.2$, $\mu C(\text{medium}) = 0.4$, $\mu C(\text{medium}) = 0.2$, and $\mu C(\text{high}) = 0.5$. These fuzzy estimates are carried over to the third step of the fuzzy logic analysis, defuzzification.

The third and last step in the fuzzy logic analysis, *defuzzification*, involves also two procedures, one is the transposition of the fuzzy estimates, and the other is the aggregation of the transposed fuzzy estimates (Fig. 5). The transposition is the reverse process of the fuzzification, hence the term defuzzification. The fuzzy estimates on the y-axis are extended horizontally to intersect the membership functions of the output index. The transposed fuzzy estimates correspond to the area under these intersections, also referred to as the truncated membership functions. In the case of the technology diffusion example, there are four (non-zero) truncated membership functions. They are labelled a, b, c and d in Fig. 5, where $a = \mu C(\text{low}) = 0.2$, $b = \mu C(\text{medium}) = 0.2$, $c = \mu C(\text{medium}) = 0.4$, and $d = \mu C(\text{high}) = 0.5$. The aggregation process defines an overall fuzzy conclusion by selecting an operator to aggregate the transposed fuzzy estimates. These operators include methods such as centre of gravity, mean of maximum, and largest of maximum to produce

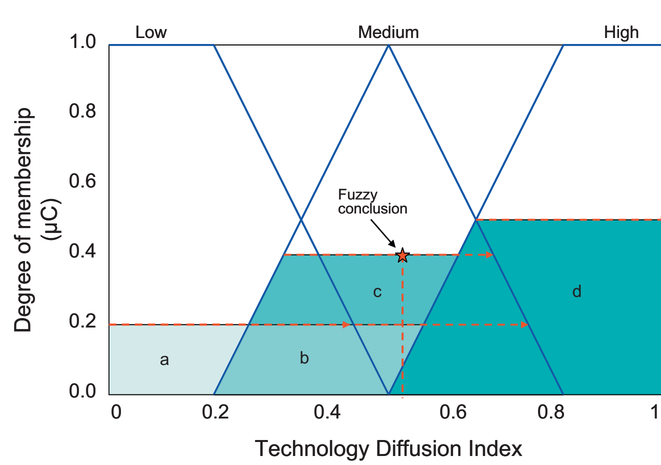

Fig. 5. Step 3 – defuzzification of the transposed fuzzy estimates.

an index with scale from 0 to 1. Fig. 5 shows the application of centre of gravity method to assess the numerical value or index of the output variable. This method divides the area under the defuzzification curve (i.e. the sum of the shaded area *a*, *b*, *c* and *d*) into two equal sub-areas. Thus, the fuzzy conclusion from 12 percent R&D investment and small-scale R&D deployment is 0.52, which is the index or trade-off parameter for technology diffusion. This index is an example output of one fuzzy model. There will be altogether 12 fuzzy models, each one aggregating the indicators for each determinant. A test of statistical correlation will be carried out before the indicators are aggregated to avoid data redundancy. The inputs for each fuzzy model are time-series data (e.g. 1970–2000) of the indicators (see examples in Table 1). They can be collected from statistics published by international and government institutions and from previous relevant studies. The preference weights for each indicator will be estimated from the conjoint analysis (see Section 4.2). The output from the fuzzy models which are indices with values ranging from 0 to 1 will be carried over as inputs to the logit analysis (see Section 4.3). The fuzzy module of, for example, MATLAB software can be used for implementing fuzzy logic analysis.

4.2. Conjoint analysis

Conjoint analysis (also known as choice models or experiments) is a practical technique not only for measuring preferences but also for developing scenario parameters. This is a technique widely used in different scientific fields including psychology, transport, economics, and environment to transform subjective choice responses into estimated parameters. Norman and Streiner [89] provide a summary of the application of conjoint analysis for environmental valuation. In conjoint analysis the attributes of an environmental good are used to understand the general trade-offs which an individual is willing to make [90]. Considerable attention has been given to this technique both in the academe and industry to measure preferences through utility tradeoffs among products and services [91,92], particularly in agro-environment (e.g. [93–96]). The subjective choices for non-economic goods and services such as those provided through the natural environment or ecosystem are valued in conjoint analysis as preferences. Public preferences have an important role in decision-making because they may in fact highlight stark policy trade-offs [97]. An environmental good can be described according to the levels of a set of attributes, and the consumer's overall judgement with respect to that product is based on these attribute levels [98]. In conjoint analysis, a set of attributes and their respective levels define the choices and thus the trade-offs. Table 2 presents examples of attributes and levels based on the determinants of economic, social and ecological sustainability. In addition, attributes on the types and sources of energy are included to give context to the choice task.

The theoretical basis for conjoint analysis is the random utility theory describing the choice behaviour of an agent in a utility maximizing framework. Based on the theory, the utility is composed of an observable or deterministic component of attributes (X_i) and an unobservable or random error component (ε_i): $U_i = \nu + \omega_1 X_1 + \cdots + \omega_n X_n + \varepsilon_i$. The $\omega_i, \ldots, \omega_n$ are the estimated weights for these attributes. There are different types of conjoint methods including Adaptive Conjoint Analysis (ACA), Traditional Full-Profile Conjoint (CVA), Choice-based Conjoint (CBC), and Partial-Profile CBC [99]. We present here an example of how to construct choice tasks for estimating preference weights using the CBC method. A choice task consists of different options, and each option in a task presents specific level of an attribute. Fig. 6 presents an example of a choice task in the survey questionnaire for conjoint analysis. The group of respondents, which can be government officials and scientists, will be asked to choose one option in the given choice task which they think is most appropriate to the current development condition and strategies of their regions or countries (e.g. question (a) in Fig. 6). The preference weights, which are the results of conjoint analysis using a choice task such as shown in Fig. 6, will be used as input to the fuzzy models in Section 4.1. If the respondents were to be given specific development and policy scenarios as context for choosing an option, the results of the conjoint analysis could be used to develop scenarios for fuzzy models (e.g. question (b) in Fig. 6). The Sawtooth software can be used not only to analyse the responses of the respondents (i.e. compute preference weights), but also to construct the choice tasks and prepare the survey questionnaire.

Table 2
Example of attributes and their levels for constructing choice tasks.

Attributes	Levels
Type of energy	(1) Bioenergy (2) Other renewables (e.g. wind, solar) (3) Fossil fuels (4) Mixed types (i.e. both fossil and renewables including bioenergy)
Source of energy	(1) Local production (2) Imported energy (raw or finished product) (3) Mixed sources (i.e. both local and imported sources)
Economic stability	(1) Achieve energy security (2) Promote technology diffusion (3) Develop market infrastructure
Social equity	(1) Ensure food security (2) Promote welfare (3) Reduce social exclusion
Resource productivity	(1) Increase feedstock supply (2) Enhance resource capacity (3) Improve land management

4.3. Spatiotemporal logit analysis

Logistic distribution function or logit model is a relevant technique to generate production activities trade-off or the probabilities of land use conversions in a geographical space. Few studies have already applied logit models on spatial data from historical land use maps to estimate the probability of land use conversions (e.g. [100,101]). In this kind of model, the dependent variable represents a finite set of alternatives that can be chosen and has a discrete statistical distribution [102]. The choices are either the presence or the absence of occurrence of land use change on a spatially explicit location. Thus, the dependent variable will be binary, taking a value of 1 when land use change occurred and 0 when it did not. In the binary choice framework, the independent variables, which are sets of variables influencing conversions from one land use to another, can have continuous or discrete distributions. Two sets of independent variables will be used to estimate the probability of land use conversions, one consists of spatial data on topographical features and soil properties, and the other is temporal data on social, economic and ecological sustainability. The logistic distribution function (logit model) is given as:

$$F(Y_t) = \frac{1}{1 + \exp(-Y_t)} \tag{1}$$

$$P(LUC_t = 1) = F(Y_t) \tag{2}$$

$$Y_t = \beta_{0t} + \beta_1 ECO_t + \beta_2 SOC_t + \beta_3 ENV_{it} + \varepsilon_t \tag{3}$$

where Y_t is the unobservable or latent variable, ECO_t is the set of parameters for economic stability at time t, SOC_t is the set of param-

Which of the following options would you choose, taking into account the given situations in (a) and (b)?

Attributes	Option1	Option 2	Option 3	Option 4
Type of energy	Bioenergy	Other renewables	Fossil fuels	Mixed types
Source of energy	Imported energy	Local production	Mixed sources	Local production
Economic Stability	Promote technology	Energy security	Develop market	Energy security
Social Equity	Promote welfare	Reduce exclusion	Food security	Promote welfare
Resource productivity	Increase feedstock	Improve management	Enhance resources	Improve management

(a) Past policies and current development condition in your country? _______________

(b) Future policy strategies and development plans in your country? _______________

Fig. 6. Example of a choice task in a survey questionnaire.

eters for social equity at time t, ENV_{it} is the set of parameters for resource productivity and spatial data on topographical features and soil properties in a geographical space i at time t, and LUC_t is the occurrence of land use change observed at time t. The presence (i.e. $LUC_t = 1$) and absence (i.e. $LUC_t = 0$) of land use change will be based on historical data on the changes in land use as shown for example in Fig. 2c. The solution to the above equations will be based on a panel regression technique given the combination of spatial and temporal data. The temporal data are trade-off parameters of economic stability, social equity and resource productivity, which will be generated from the fuzzy logic analysis. Using fuzzy-generated parameters will simplify the model specifications considering the large number and diverse types (i.e. both quantitative and qualitative) of indicators that measure these determinants. To create the spatial dataset from the land use, topographical and soil maps, a sample of one point per unit of land (e.g. hectare) will be drawn out from each GIS map. The sample points should be identical for all the maps.[4] The data for the dependent variable LUC_t consist of the most relevant land use change trajectories (e.g. crops to biofuel plantation (*CR–BP*)) observed from land use maps in a particular case study region for different periods. The logit models will generate as outputs the probabilities of land use conversions ranging from zero to 100 percent (where zero means low and 100 percent means high probability), which can be mapped out to show spatial distribution of probabilities. In the STRAP approach, these probabilities not only summarise the past developments, but also inform about the possible future trend (i.e. potentials) in a specific land use conversion. The latter is based on the assumption in economic analysis that, holding other things constant, the developments in the past (i.e. as estimated in time-series regression) will tend to continue in the future. This assumes of course that no structural adjustments will take place through major policy changes. For each land use conversion, alternative model specifications will be tested. The best model specifications with the highest number of suitable coefficients (i.e. statistically significant, correct signs) will be carried over as inputs to the path analysis. Standard statistical software such as SPSS and SAS can be used to estimate logit models.

5. Path analysis and bioenergy pathways

Path analysis is a useful technique in determining development pathways for bioenergy production. Its technique was developed by Sewall Wright in the 1920s to investigate ramifications of various models in population genetics [103], and since then is used extensively in the fields of social science (see examples in Stage et al. [104]). The extension of the technique to provide solutions to more intricate model decomposition led to the evolution of path analysis to what is now called the structural equation model (SEM). SEM is a research technique that is mostly applied in psychology, sociology, biological sciences, educational research, political science and marketing research since the 1970s [105]. More recently, path analysis and its SEM extension have been applied in the field of resource or environmental economics in particular on land use (e.g. [100,105,106]). Because path analysis is simpler to illustrate than SEM and provides the basic technique for SEM, the discussion here progresses from the basics of the path analysis to the sophistications of the SEM. Path analysis aims to provide estimates of the magnitude and significance of hypothesized causal connections among sets of variables displayed through the use of path diagrams [104]. A path diagram has three components: (1) variables, (2) arrows, and (3) coefficients (Fig. 7). The variables (e.g. Xs and Y) are those identified to have relations in the model, either causal or correlations. The arrows point from one variable to another to show the type of relations: a single-headed arrow shows causal relations and a double-headed, curved arrow shows correlations. The coefficients (e.g. β_1, β_2, β_3), which are estimates from multiple regression analysis show the relative importance of causal paths of the exogenous to the endogenous variables. Because path analysis makes use of the regression estimates, it is referred to as an extension of regression techniques. However, the independent or explanatory variables are called exogenous variables (e.g. X_1, X_2, X_3) in path analysis, and the dependent variables are called endogenous variables (e.g. Y). Path analysis is sensitive to model specification because, as in regressions, exclusion of relevant causal variables or inclusion of irrelevant variables can affect path coefficients [104]. It is thus important to assess alternative model specifications on the basis of their goodness of fit. To simplify the illustration of alternative model specifications, first we use in Fig. 7 only the determinants of economic stability (i.e. exogenous variables) to explain the probability of land use conversion from crops to biofuel plantations (i.e. endogenous variable). The three models in Fig. 7a–c differ in terms of the structure of relationships of the exogenous to the endogenous variables. Three types of effects are measured in path analysis: total, direct and indirect effects [107]. The total effect (ρ), usually written on top of the endogenous variable, informs how much change in endogenous variable is induced by a given change in the exogenous variables. The direct effect is part of the total effect which is not transmitted via intervening variables (Fig. 7a). The indirect effects are those parts of the total effect which are transmitted or mediated by variables specified as intervening between the cause and the effect in a model. The intervening variable in Fig. 7b is X_3 and those in Fig. 7c are X_2 and X_3.

Fig. 8 shows a complete path analysis of economic, social and ecological determinants of sustainability based on the model specification in Fig. 7a. This model specification assumes that the different determinants not only in each sustainability pillar but also across the three sustainability pillars are correlated. Moreover, all

[4] By taking such a sample, overestimations of the level of statistical significance will be avoided. This would be the case if all pixels that represent one single land use change event were counted as individual observations.

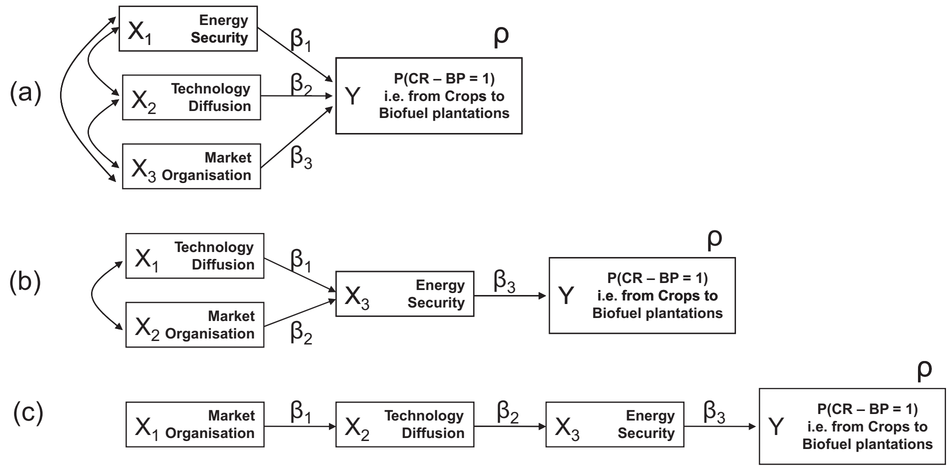

Fig. 7. Possible relations of determinants of economic stability to a land use conversion.

the determinants have direct effects on the probability of land use conversion *CR–BP* (i.e. $\beta_1, \ldots, \beta_9 \neq 0$) and that the linear sum of all direct path coefficient β_s should be equal to the total direct effect (i.e. $\sum_{i=1}^{n} \beta_i = \rho$). Because resource endowments and development strategies vary, the total effect of exogenous on the endogenous variables (i.e. ρ), the values of path coefficients (i.e. $\beta_1, \ldots, \beta_9$), and the directions of path relations (e.g. Fig. 7a–c) are expected to vary in different regions or countries. In some cases, the path relations between the exogenous variables (e.g. $X_1, \ldots, X_9$) and the endogenous variable (i.e. *CR–BP*) are not simply direct causal effects as illustrated in Fig. 8. Depending on the complexity of the path relations, there may be a need to proceed from path analysis to structural equation model (SEM). Fig. 9 illustrates a case where the probability of land use conversion is determined not directly by the observable determinants or measured variables (i.e. $X_1, \ldots, X_9$) but by some unobservable factors (i.e. Y_1, Y_2, and Y_3), which in turn are defined by the relationships between the relevant measured variables. These unobservable factors are referred to as latent variables and considered as endogenous variables because they are estimated in SEM. SEM is thus a hybrid model with both multiple determinants for each latent variable and specific paths connecting to the latent variables; it is considered a useful technique because it can deal with several directions of influence between variables [105], both measured and latent. Inclusion of latent variables could be useful for considering simultaneously a number of measures for the same construct and for reducing unreliability of measured variables especially those with qualitative data [89]. Following the sustainability concept in Section 3, the latent variables are represented by economic stability (Y_1), social equity (Y_2), and resource productivity (Y_3). They are assumed to have direct paths to the probability of land use conversion and thus serve as intervening variables to the measured variables (i.e. determinants). Moreover, because they could influence each other, they also have indirect paths to the probability of land use conversion. The total effect to the probability of land use conversion is thus the additive values of all α and β coefficients (i.e. $\sum_{i=1}^{n} \alpha_i + \beta_i = \rho_1$). In addition to the path coefficients, the model specification in Fig. 9 will generate estimates not only for the probability of land use conversion (ρ_4), but also for economic stability (ρ_1), social equity (ρ_2), and resource productivity (ρ_3). These latter three estimates provide a measure of the influence of the sustainability pillars on the bioenergy potentials.

The path diagrams in Figs. 8 and 9 are examples of outputs from the path analysis and its SEM extension. In these diagrams, the development pathways for bioenergy production will be defined by not only the path relations and directions, but also the values of coefficients and their total effects on the land use conversions. The higher these values the higher are the potentials for bioenergy production. The pathway diagrams are a convenient tool for identifying the most relevant social, economic and ecological determinants that influence bioenergy potentials. The data inputs for the path analysis are the estimates from and specification of the logit models, which in turn use parameters from fuzzy models as data inputs. This hybrid approach thus takes into consideration the trade-offs between the sustainability determinants (output from the fuzzy models), albeit indirectly, and production activities (output from the logit models) in identifying development pathways for bioenergy production. The models specified in both Figs. 8 and 9 can be solved using SPSS, which has statistical packages (e.g. LISREL and AMOS) for doing path analysis and SEM.

6. Illustration of empirical applications

To illustrate the empirical application of the parameterisation techniques for generating trade-off parameters and path analysis for identifying bioenergy pathways, we present below results of relevant studies.

6.1. Fuzzy indices

Using fuzzy logic models, Acosta-Michlik et al. [87] computed indices for the determinants of socio-economic susceptibility[5] to droughts in selected regions in India, Portugal and Russia. The determinants for economic development include financial resources, agriculture sector, infrastructure system, and those for social well-being include educational attainment, health status and gender equality. The area in web diagrams in Fig. 10 measures socio-economic susceptibility based on these determinants. The level of susceptibility increases from the centre to the edge of the web, thus the larger the area in the web the higher is the susceptibility. The region of Andhra Pradesh in India had the highest overall socio-economic susceptibility in the first half of the 1990s. As compared with other case study regions, Andhra Pradesh had the lowest educational attainment and the poorest health condition contributing to its high socio-economic susceptibility. In contrast, however, the susceptibility in terms of infrastructure development was low-

[5] Socio-economic susceptibility is defined as the inability of the state and society to protect and support communities from adverse water stress if market mechanisms fail to provide the necessary resources for coping with the stress [87].

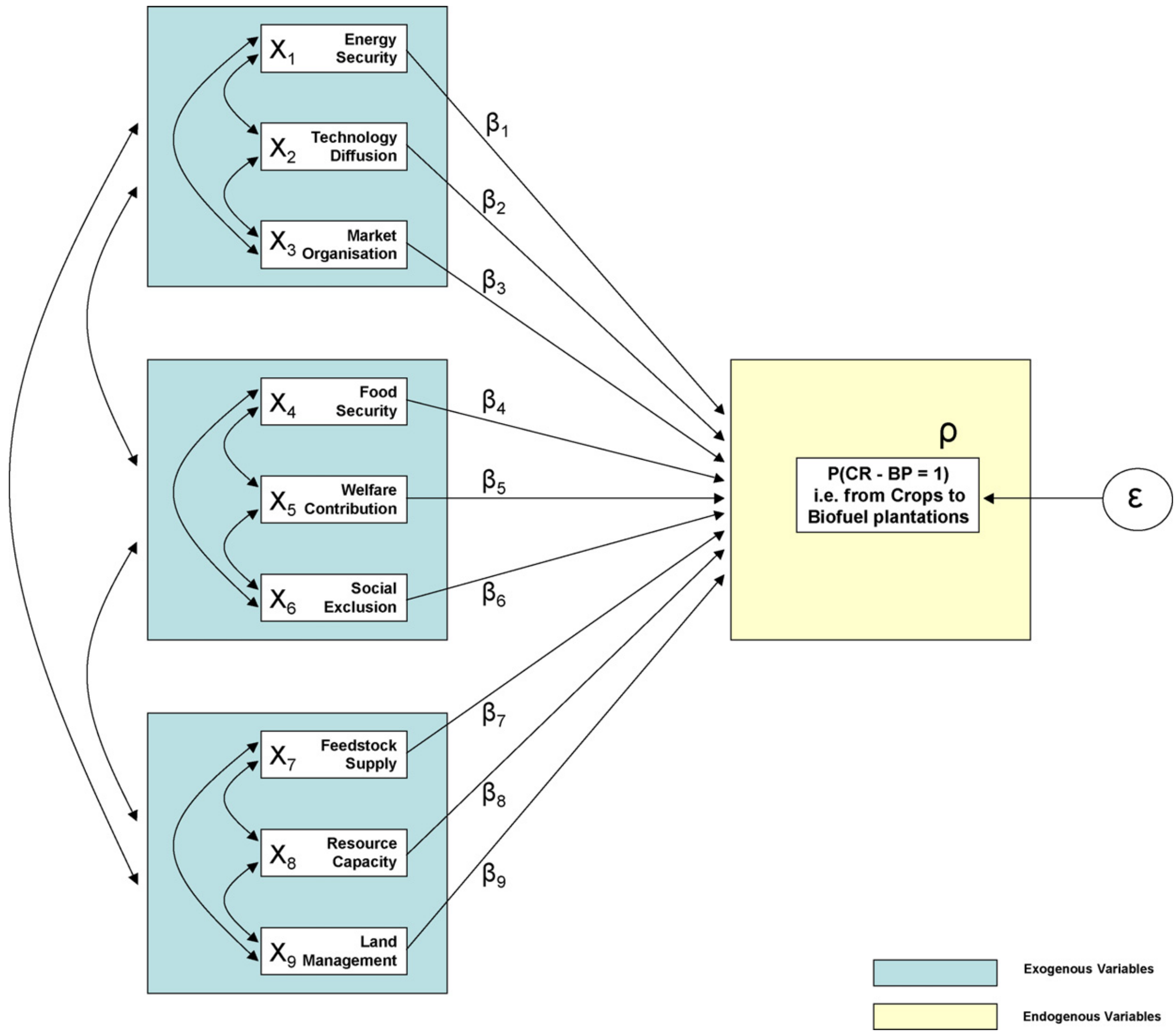

Fig. 8. Path analysis of economic, social and ecological determinants for crops to biofuel conversion.

est in Andhra Pradesh, India. The extensive irrigation programme of the Indian government in the past as a measure to promote agricultural development contributed to a good agricultural infrastructure [87]. The results of the fuzzy analysis in this study thus indicate that the government in India has traded-off agricultural development against education and health well-being, most likely because of the large number of people who depend on agriculture for their income and livelihood. Looking at the trend in the determinants of socio-economic susceptibility, a somewhat different conclusion can be deduced. Fig. 11 shows that the level of economic development continuously decreased in India from 1980 to 1995, reaching the lowest level in the early 1990s due to the impacts of the 1991 global economic crisis. However, the level of social well-being in India did not change significantly. This implies that, whilst social support in India is low as compared to Portugal and Russia, the government in the former country did not trade-off social well-being in periods of low economic growth. This illustration of fuzzy logic application shows the usefulness of the technique in assessing trade-offs between different determinants of a particular system. Although Acosta-Michlik et al.'s focus of analysis is human susceptibility to the impacts of droughts, their framework is based on the sustainability concept [88]. They essentially draw on the work of Cornelissen et al. [86] which develop fuzzy mathematical models to assess sustainable development based on context-dependent economic, ecological, and societal sustainability indicators. Acosta-Michlik et al. [108] show that fuzzy indices can be used as data inputs to logit models. They use the fuzzy indices of socio-economic susceptibility and the indices of water stress [109] as independent variables (Fig. 11), and the occurrence of drought crisis (i.e. crisis event = 1, no crisis event = 0) as dependent variable to logit models. Because we are interested in the application of logit models using not only time-series but also spatial data to allow for the generation of probability maps (Section 6.3), we refer below to another study for the application of logit models. Moreover, because relative weights of the different determinants in the fuzzy logic analysis were not explicitly modelled in Acosta-Michlik et al. [87], we also refer to another study on how to estimate the weights that measure policy preferences.

6.2. Weighing preferences

Using conjoint analysis, Sydorovych and Wossink [110] selected economic, social, and ecological attributes that are perceived as important for agricultural sustainability by different stakeholders and assessed their relative impacts/weights on the overall sustainability measure. They argue that the method presents a theoretically founded framework to elicit peoples' perceptions of sustainability and relative weights of its different attributes. Their study is the first application of conjoint analysis to elicit relative weights of the various attributes of agricultural sustain-

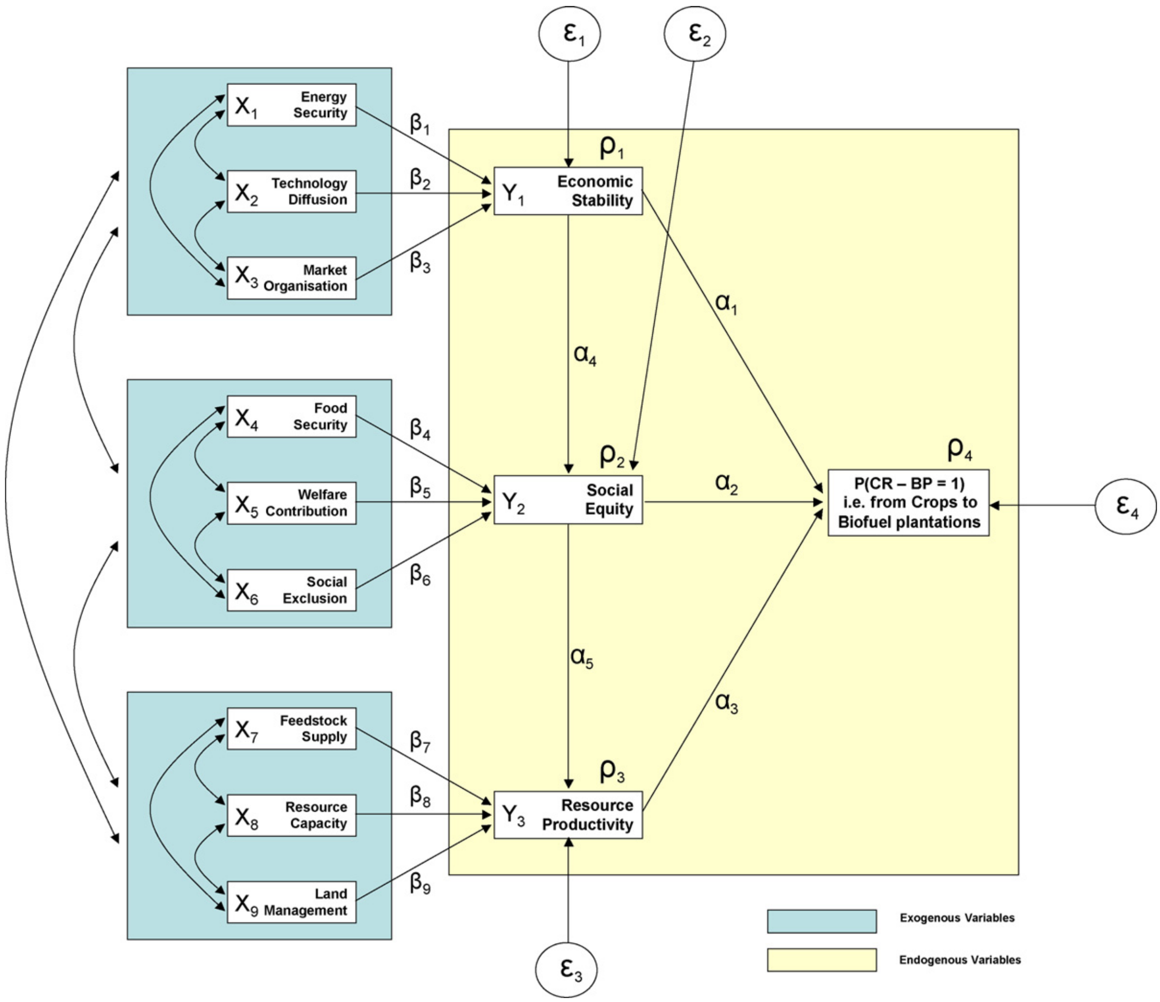

Fig. 9. SEM analysis of economic, social and ecological determinants for crops to biofuel conversion.

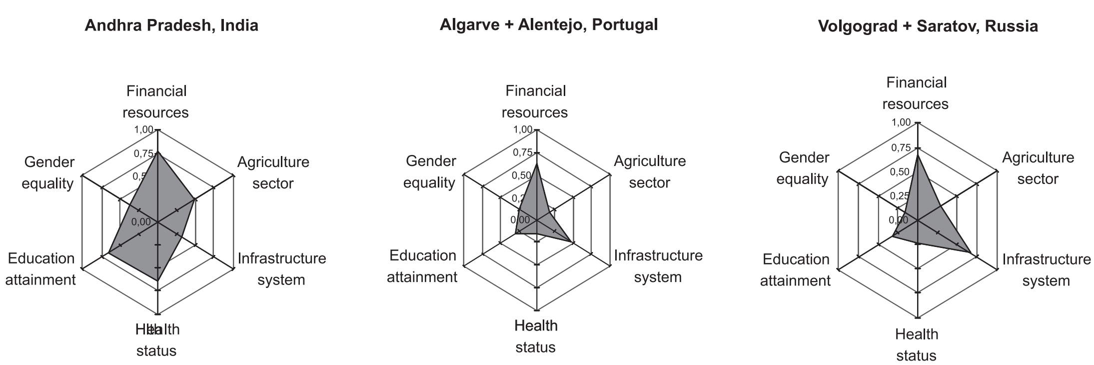

Fig. 10. Indices of determinants of economic development and social well-being, 1991–1995.

Source: Acosta-Michlik et al. [87].

ability. A total of 480 surveys were distributed to farmers and scientists with a response rate of 25 percent. Table 3 presents the estimation results with significant coefficients for the entire sample. Sydorovych and Wossink [110] present all attributes on a uniform scale so that estimated coefficients directly indicate relative impact of corresponding attributes on sustainability. For example, the relative weight of long-run profit prospects on economic sustainability is calculated as the coefficient on this attribute divided by a sum of all statistically significant coefficients on economic sustainability attributes: $\omega_k = \hat{\beta}_k / \sum_{k=1}^{K} \hat{\beta}_k$; $\omega_{\text{long-run profit}} = 1.85/(1.85 + 0.49 + 0.66) = 0.63$. The results suggest that the most important indicator for economic sustainability is the prospects for long-run profit (63 percent), for social sustainability it is the safety of products to consumers (53 percent), and for ecological sustainability it is quality of surface and ground water (44 percent). Sydorovych and Wossink [110] conclude from the conjoint results that respondents, when facing a choice situation, are willing to make trade-offs among attributes; they accept an undesirable value of attribute less important to them for a desirable value of an attribute that is very important. This study illustrates

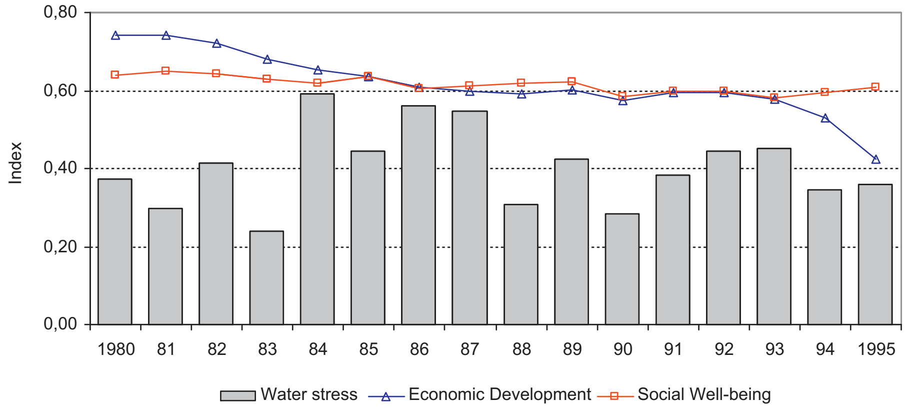

Fig. 11. Indices of determinants of socio-economic susceptibility for India, 1980–1995.
Data sources: Acosta-Michlik et al. [87]; Alcamo et al. [109].

Table 3
Preference weights for indicators of agricultural sustainability.

Attributes	Levels	Coefficients	Weights
Economic sustainability			
Prospects for long-run profit	Good prospects; odds are against long-run profits	1.85***	0.63
Reliance on purchased inputs	Moderately reliant; highly reliant	0.49**	0.16
Extent of governmental regulations	Easy to comply; difficult to comply	0.66***	0.21
Social sustainability			
Internal			
Physical stress	Moderate; high	0.64***	0.15
Mental stress	Moderate; high	1.54***	0.35
Known health risks	Safe; potential risk involved	0.95***	0.22
Farm will remain in the family after farmer retires	Yes; no	1.24***	0.28
External			
Safety of product to consumers	Safe; potential risk involved	2.24***	0.53
Product nutrition/quality/taste	Enhanced; not enhanced	1.02***	0.22
Visual attractiveness of production/odors/noise	Considered pleasant; considered unpleasant by some people	0.56**	0.12
Use of information	Farmer uses/shares information; farmer depends on own knowledge	0.57***	0.12
Ecological sustainability			
Soil quality	Enhanced; maintained, not enhanced	0.49**	0.09
Surface water quality	Safe; potential risk involved	1.23***	0.23
Groundwater quality	Safe; potential risk involved	1.13***	0.21
Agro and natural biodiversity	Enhanced; not enhanced	0.52**	0.09
Disposal of solid waste	Properly disposed; improperly disposed	1.03***	0.19
Air quality	Safe; potential risk involved	0.41*	0.07
Emissions of greenhouse gases	Reduced; not reduced	0.63**	0.11

Source: Sydorovych and Wossink [110].
Note: The coefficients are the estimation results and the weights (or mean attribute weights) are the attribute's relative impact. The weights might not add to one due to rounding.
* Coefficients significantly different from zero at $a = 0.1$.
** Coefficients significantly different from zero at $a = 0.05$.
*** Coefficients significantly different from zero at $a = 0.01$.

the usefulness of the technique in estimating the weights that are needed to realistically represent the policy preferences and sustainability trade-offs in the fuzzy logic analysis. Combining conjoint weights to improve fuzzy logic analysis has not been so far explored elsewhere.

6.3. Probability maps

Using logit models, Bakker et al. [100] developed probability maps for land use change in Greece using soil depth, erosion and slope as independent variables. They considered two land use changes, reallocation of rangeland to cereal cultivation and abandonment of areas under cereals. As explained by Acosta-Michlik et al. [101], the socio-economic characteristics of the farmers could also be combined with biophysical characteristics of the farms as explanatory variables in developing probabilities of land use conversions. Although Acosta-Michlik et al.'s methods are more related to those suggested in this paper, we illustrate here Bakker et al.'s application of logit models because they further used the logit results for the path analysis (see Section 6.4). The latter tested a total of 14 model specifications for both abandonment of and reallocation to cereals using land use maps from the year 1886 and 1996 as data for the dependent variable, and maps of soil depth, erosion and slope for the same years as data for independent variables. The optimal model for estimating the probabilities of reallocation of rangeland to cereals is given as: $logit[Pr(reallocation)] = -2.0695 - 0.2332X_1 + 2.0517X_2$; where X_1 is slope and X_2 soil depth [100, p. 476]. Substituting the 1996 spatial data (scale of 1:50,000) for slope and soil depth generates the probability map for abandoning cereals in Fig. 12. Because the probability maps are estimates from historical transition of land uses, they represent how production activities are traded-off against one another (in this example, from rangelands to cereals) due to economic, social or environmental reasons. In case of reallocating

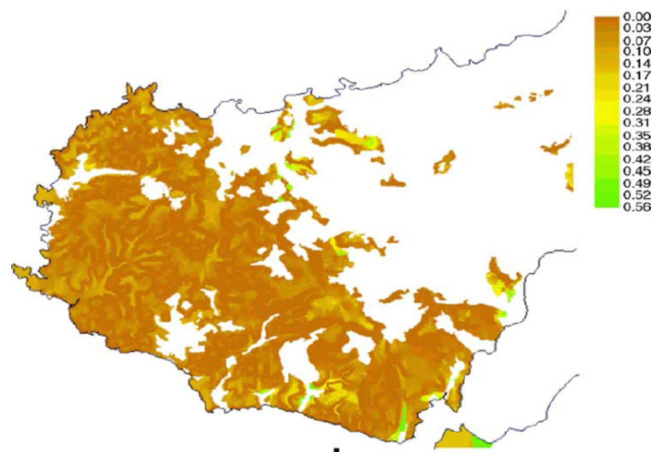

Fig. 12. Probabilities of the reallocation of rangeland to cereals in Lesvos, Greece. *Source:* Bakker et al. [100].

rangeland to cereals, the significance of soil depth as independent variable relates to the marginal productivity of the land, i.e. shallow soils are less productive because there are fewer nutrients available for the crops. Bakker et al. [100, p. 480] use Fig. 12 to describe the future perspectives or potentials for reallocating rangelands to cereals: "under current conditions . . . current rangelands have no potential for cereal cultivation" given the probabilities of mostly below 50 percent. Thus, in addition to trade-offs, the probability maps are a useful measure of land use potentials. What influences these potentials can be further investigated through path analysis.

6.4. Path relations and directions

Whilst the logit model specification above shows that slope and soil depth are the only significant variables for predicting the reallocation of rangelands to cereals, the path analysis reveals that soil erosion also influences this land use change, albeit indirectly (Fig. 13). The computed sum of the relevant path coefficients is given as: $0.31 \times 533.943 + 0.40 \times 63.266 + 0.60 \times 63.266 + 422.452 = 960.356$ [100, p. 480]. The coefficient values in Fig. 13 reveal that 60 percent of the effects of erosion on the reallocation of rangelands to cereals is transmitted through soil depth, and only 40 percent is direct effect. Bakker et al. explain that the former relates to the reduction in soil depth affecting rooting depth and soil moisture, and the latter represents the removal of organic matter and water-

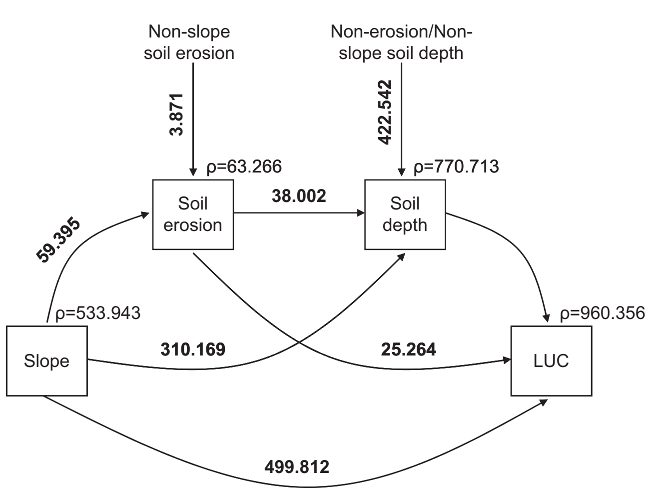

Fig. 13. Path analysis for the reallocation of rangeland to cereals in Lesvos, Greece. *Source:* Bakker et al. [100].

holding capacity and increased stoniness due to selective removal of fine soil particles. Because soil erosion is in the middle of a "chain of drivers", they also clarify that it has no added value as predictor when combined with both slope and soil depth, i.e. the potential effect of erosion on land use change is already included in the two other variables. These results have important implications for policy. Whilst soil erosion does not directly influence land use change, measures to prevent soil erosion can improve soil depth, which in turn can either enhance reallocation of land into or reduce abandonment of land planted to cereals. In doing so, cure is provided to the roots and not to the possible symptoms of the problem. In assessing bioenergy pathways, this is particularly important due to the complex interrelationships between a large number of determinants for sustainable bioenergy production. Thus, using path analysis one can identify the scale and direction of influences of the selected determinants that are otherwise excluded from simple logit analysis. Moreover, Fig. 13 reveals that explanatory variables not previously considered in the conceptual model can be identified through the path analysis. In analysing the path of reallocating rangelands to cereals, Bakker et al. [100] identified "non-slope erosion" as well as "non-erosion and non-slope soil depth" as additional variables in the path analysis. This process is quite useful in the context of bioenergy where the concept of sustainability is not yet fully developed. In analysing the path from traditional land uses to modern bioenergy production, it is thus likely to identify unknown variables.

7. Conclusions

Renewable energy sources (e.g. solar, wind, hydropower, biomass, etc.) are receiving significant policy support due to their promising contribution to climate change mitigation. Moreover, these contemporary sources of energy could contribute to sustainable development because of their potential benefits on the environmental as well as the socio-economic system. Among these renewable sources, energy from biomass has the largest impacts on local communities in many, if not all parts, of the world because of its direct effects on rural livelihood and employment, food availability and accessibility, fresh water supply, social exclusion and lifestyle changes. Current controversies and debates on the role of bioenergy not only on these socio-economic issues but also on GHG emission reduction, which is the early key motivation for renewable energies, are reminders of the challenges to be dealt with for bioenergy sector to develop and thrive. In view of these challenges, it is important to create a framework for evaluating the regional and region-specific sustainability of the potential production across the sustainability pillars. To date such a broad framework does not exist. In this paper, we developed a framework describing how one could assess trade-offs and pathways for a sustainable bioenergy production. The foci of the framework are trade-offs and pathways because bioenergy competes with other land uses and offers alternative feedstock sources and conversion technologies, which then provide different regions the options to pursue different strategies to develop their domestic bioenergy sector. Although a large amount of literature has emerged on bioenergy potentials in recent years, only few mention pathways to sustainable bioenergy development (e.g. [11,35,111,112]). Some studies provide conceptual design, but they lack empirical methods to systematically assess pathways particularly those resulting from trade-off decisions in bioenergy production.

To fill this research gap, we presented a hybrid approach as a roadmap toward application of this framework in regions with diverging economic, social and ecological systems. The approach is a fusion of diverse techniques which, when applied separately to assess the sustainable development of bioenergy, will fail to

capture the complex system of bioenergy production. Fuzzy logic technique can generate indices of sustainability from a wide range of qualitative and quantitative indicators, but by itself ignores the real trade-off decisions on these indicators and the spatiotemporal interdependencies of these decisions. Conjoint analysis can generate estimate of the former and logit analysis can provide estimate of the latter. Conjoint technique has been applied separately to assess sustainability, but such a simplistic assessment does not take into account the array of information in temporal and spatial data. Logit technique can estimate bioenergy potentials based on the interdependencies between the temporal indicators and land use maps, but this technique alone cannot consider and identify the interconnections among the economic, social and ecological determinants of sustainability. These interconnections represent the issues and concerns (e.g. energy versus food security, first versus second generation bioenergy, etc.) that are relevant in the sustainability assessment of bioenergy. The conceptual links between these determinants of sustainability can be taken into consideration using the logical aggregation techniques in fuzzy logic analysis and can be validated using the logical variable relations in path analysis. Through the integration of the knowledge generated from each of these techniques, the hybrid approach combines qualitative and quantitative information, temporal and spatial scales, and opportunities and dilemmas in bioenergy production, all of which are mutually important to measuring the interconnections and interdependencies among the different sustainability determinants for bioenergy.

However, improving the relevance and validity of the results using such an integrated assessment approach has a price. The hybrid approach ideally requires a large amount of time-series data, various GIS maps with reasonable resolutions, and dedicated stakeholders for the survey. Therefore, collection and processing of the data could be time- and money-wise demanding. In many, if not most applications, not all of these different types and sources of data will be available or easily accessible so that reduced variants of the framework have to be considered. Future research should address the minimum data requirements that will allow the use of the hybrid approach for interregional comparison of bioenergy potentials under data constraints. In this paper, the hybrid approach follows a step-by-step procedure to minimise disparate and inconsistent results due to partial information or biased analysis. An assessment that is as comprehensive as possible is very relevant and timely. This is because the bioenergy sector is strongly expanding and thus likely to affect all other sectors of the economy and a large number of the population globally. Wise decisions about future land use require a comprehensive analysis in order to avoid detrimental lock-ins and surprising outcomes later.

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References

[1] Doornbosch R, Steenblik R. Biofuels: is the cure worse than the disease? Paris: OECD; 2007.
[2] Cotula L, Dyer N, Vermeulen S. Fuelling exclusion? The biofuels boom and poor people's access to land. London: IIED; 2008.
[3] Rosegrant MW. Biofuels and grain prices: impacts and policy responses. Washington: International Food Policy Research Institute; 2008.
[4] Buerkert A, Schlecht E. The biofuel debate– status quo and research needs to meet multiple goals of food, fuel and ecosystem services in the tropics and subtropics. J Agric Rural Dev Trop Subtrop 2009;110:1–8.
[5] Fargione J, Hill J, Tilman D, Polasky S, Hawthorne P. Land clearing and the biofuel carbon debt. Science 2008;319:1235–8.
[6] Searchinger T, Heimlich R, Houghton RA, Dong F, Elobeid A, Fabiosa J, et al. Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. Science 2008;319:1238–40.
[7] Lapola DM, Schaldach R, Alcamo J, Bondeau A, Koch J, Koelking C, et al. Indirect land-use changes can overcome carbon savings from biofuels in Brazil. PNAS 2010;107:3388–93.
[8] Clancy JS. Are biofuels pro-poor? Assessing the evidence. Eur J Dev Res 2008;20:416–31.
[9] Mathews JA. Opinion: is growing biofuel crops a crime against humanity? Biofuels Bioprod Biorefin 2008;2:97–9.
[10] Sawyer D. Climate change, biofuels and eco-social impacts in the Brazilian Amazon and Cerrado. Philos Trans R Soc Lond B: Biol Sci 2008;363:1747–52.
[11] Faaij AP. Bio-energy in Europe: changing technology choices. Energy Policy 2006;34:322–42.
[12] Naylor RL, Liska AJ, Burke MB, Falcon WP, Gaskell JC, Rozelle SD, et al. The ripple effect: biofuels, food security and the environment. Environment 2007;49:30–43.
[13] Braun JV. When food makes fuel: the promises and challenges of biofuels. Food Policy 2007:1–9.
[14] Lustig N. Thought for food: the challenges of coping with soaring food prices. Working Paper Number 155, Center for Global Development, Washington; 2008.
[15] Brühl CA, Eltz T. Fuelling the biodiversity crisis: species loss of ground-dwelling forest ants in oil palm plantations in Sabah, Malaysia (Borneo). Biodivers Conserv 2010;19:519–29.
[16] Ceccon E, Miramontes O. Reversing deforestation? Bioenergy and society in two Brazilian models. Ecol Econ 2008;67:311–7.
[17] Sasaki N, Knorr W, Foster DR, Etoh H, Ninomiya H, Chay S, et al. Woody biomass and bioenergy potentials in Southeast Asia between 1990 and 2020. Appl Energy 2009;86:S140–50.
[18] Butler RA, Laurance WF. Is oil palm the next emerging threat to the Amazon? Trop Conserv Sci 2009;2:1–10.
[19] Jumbe CB, Msiska FB, Madjera M. Biofuels development in sub-Saharan Africa: are the policies conducive? Energy Policy 2009;37:4980–6.
[20] Hall J, Matos S, Severino L, Beltrao N. Brazilian biofuels and social exclusion: established and concentrated ethanol versus emerging and dispersed biodiesel. J Cleaner Prod 2009;17:S77–85.
[21] Ariza-Montobbio P, Lele S. Jatropha plantations for biodiesel in Tamil Nadu, India: viability, livelihood trade-offs, and latent conflict. Ecol Econ 2010;70:189–95.
[22] Barbier EB. The concept of sustainable economic development. Environ Conserv 1987;14:101–10.
[23] Dovers SR. Sustainability: demands on policy. J Public Policy 1997;16: 303–18.
[24] Pope J, Annandale D, Morrison-Saunders A. Conceptualising sustainability assessment. Environ Impact Assess Rev 2004;24:595–616.
[25] Gibson RB. Beyond the pillars: sustainability assessment as a framework for effective integration of social, economic and ecological considerations in significant decision-making. J Environ Assess Policy Manage 2006;8:259–80.
[26] Gasparatos A, El-Haram M, Horner M. A critical review of reductionist approaches for assessing the progress towards sustainability. Environ Impact Assess Rev 2008;28:286–311.
[27] Wiley JB. Reliability and cross-validity of trade-off analysis in an industrial setting. J Bus Res 1981;9:283–95.
[28] Banerjee P, Heim JA. An economic trade-off analysis experiment for integrating manufacturing systems computer software. Comput Ind Eng 1994;26:511–20.
[29] Nord E. The trade-off between severity of illness and treatment effect in cost-value analysis of health care. Health Policy 1993;24:227–38.
[30] Christakis DA, Harvey E, Zerr DM, Feudtner C, Wright JA, Connell FA. A trade-off analysis of routine newborn circumcision. Pediatrics 2000;105: 246–9.
[31] DeVoil P, Rossing W, Hammer G. Exploring profit – sustainability trade-offs in cropping systems using evolutionary algorithms. Environ Model Softw 2006;21:1368–74.
[32] Sattler C, Schuler J, Zander P. Determination of trade-off-functions to analyse the provision of agricultural non-commodities. Int J Agric Resour Gov Ecol 2006;5:309–25.
[33] Gibson R, Hassan S, Holtz S, Tansey J, Whitelaw G. Sustainability assessment: criteria and processes. London: Earthscan; 2005.
[34] Guest R. The economics of sustainability in the context of climate change: an overview. J World Bus 2010;45:326–35.
[35] Kaditi EA. Bio-energy policies in a global context. J Clean Prod 2009;17:4–8.
[36] Oxford dictionaries online. Oxford University Press; 2010.
[37] Cambridge dictionary online. Cambridge University Press; 2010.
[38] Demirbas A. Biorefineries: current activities and future developments. Energy Convers Manage 2009;50:2782–801.
[39] Hamelinck CN, Faaij AP. Outlook for advanced biofuels. Energy Policy 2006;34:3268–83.
[40] Girard P, Fallot A. Review of existing and emerging technologies for the production of biofuels in developing countries. Energy Sustain Dev 2006;X:92–108.
[41] Eickhout B, Van Den Born G, Notenboom J, Van Oorschot M, Ros J, Van Vuuren D, et al. Local and global consequences of the EU renewable directive for

biofuels: testing the sustainability criteria. In: MNP report. Netherlands Environmental Assessment Agency; 2008, 70 pp.
[42] Zah R, Ruddy TF. International trade in biofuels: an introduction to the special issue. J Clean Prod 2009;17:1–3.
[43] Hansson J, Berndes G. Future bioenergy trade in the EU: modelling trading options from a cost-effectiveness perspective. J Clean Prod 2009;17:27–36.
[44] Ravindranath NH, Balachandra P. Sustainable bioenergy for India: technical, economic and policy analysis. Energy 2009;34:1003–13.
[45] Rosillo-Calle F, Walter A. Global market for bioethanol: historical trends and future prospects. Energy Sustain Dev 2006;X:20–32.
[46] Mayfield CA, Foster CD, Smith CT, Gan J, Fox S. Opportunities, barriers, and strategies for forest bioenergy and bio-based product development in the Southern United States. Biomass Bioenergy 2007;31:631–7.
[47] Londo M, Lensink S, Wakker A, Fischer G, Prieler S, Velthuizen HV, et al. The REFUEL EU road map for biofuels in transport: application of the project's tools to some short-term policy issues. Biomass Bioenergy 2010;34:244–50.
[48] McCormick K, Kaberger T. Key barriers for bioenergy in Europe: economic conditions, know-how and institutional capacity, and supply chain coordination. Biomass Bioenergy 2007;31:443–52.
[49] Altman I, Johnson T. The choice of organizational form as a non-technical barrier to agro-bioenergy industry development. Biomass Bioenergy 2008;32:28–34.
[50] Faaij AP, Domac J. Emerging international bio-energy markets and opportunities for socio-economic development. Energy Sustain Dev 2006;X:7–19.
[51] Ewing M, Msangi S. Biofuels production in developing countries: assessing tradeoffs in welfare and food security. Environ Sci Policy 2009;12:520–8.
[52] Coleman MD, Stanturf JA. Biomass feedstock production systems: economic and environmental benefits. Biomass Bioenergy 2006;30:693–5.
[53] Rösch C, Kaltschmitt M. Energy from biomass – do non-technical barriers prevent an increased use? Biomass Bioenergy 1999;16:347–56.
[54] Hughes E. Biomass cofiring: economics, policy and opportunities. Biomass Bioenergy 2000;19:457–65.
[55] Junfeng L, Runqing H. Sustainable biomass production for energy in China. Biomass Bioenergy 2003;25:483–99.
[56] Thornley P, Cooper D. The effectiveness of policy instruments in promoting bioenergy. Biomass Bioenergy 2008;32:903–13.
[57] Elghali L, Clift R, Sinclair P, Panoutsou C, Bauen A. Developing a sustainability framework for the assessment of bioenergy systems. Energy Policy 2007;35:6075–83.
[58] Heinimo J, Junginger M. Production and trading of biomass for energy – an overview of the global status. Biomass Bioenergy 2009;33:1310–20.
[59] Lewandowski I, Faaij A. Steps towards the development of a certification system for sustainable bio-energy trade. Biomass Bioenergy 2006;30:83–104.
[60] Hazell P, Pachauri RK. Overview. In: Hazell P, Pachauri RK, editors. Bioenergy and agriculture: promises and challenges. Washington: IFPRI; 2006. p. 3–4.
[61] Ugarte DG. Developing bioenergy: economic and social issues. In: Hazell P, Pachauri RK, editors. Bioenergy and agriculture: promises and challenges. Washington: IFPRI; 2006. p. 5–6.
[62] Rist L, Feintrenie L, Levang P. The livelihood impacts of oil palm: smallholders in Indonesia. Biodivers Conserv 2010;19:1009–24.
[63] Larson ED, Kartha S. Expanding roles for modernized biomass energy. Energy Sustain Dev 2000;IV:15–25.
[64] Godfray HC, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, et al. Food security: the challenge of feeding 9 billion people. Science 2010;327: 812–8.
[65] Garcez CA, Vianna JN. Brazilian biodiesel policy: social and environmental considerations of sustainability. Energy 2009;34:645–54.
[66] Van Wey L. Social and distributional impacts of biofuel production. In: Howarth R, Bringezu S, editors. Biofuels: environmental consequences and interactions with changing land use. Proceedings of the scientific committee on problems of the environment (SCOPE) international biofuels project rapid assessment. 2009. p. 205–14.
[67] Karekezi S, Kithyoma W. Bioenergy and the poor. In: Hazell P, Pachauri R, editors. Bioenergy and agriculture: promises and challenges. Washington: IFPRI; 2006. p. 23–8.
[68] Dufey A, Vermeulen S, Vorley W. Biofuels: strategic choices for commodity dependent developing countries. Amsterdam: Common Fund for Commodities; 2007.
[69] Pachauri S, Mueller A, Kemmler A, Spreng D. On measuring energy poverty in Indian households. World Dev 2004;32:2083–104.
[70] Demirbas AH, Demirbas I. Importance of rural bioenergy for developing countries. Energy Convers Manage 2007;48:2386–98.
[71] Anker-Nilssen P. Household energy use and the environment—a conflicting issue. Appl Energy 2003;76:189–96.
[72] Kishore V, Bhandari PM, Gupta P. Biomass energy technologies for rural infrastructure and village power—opportunities and challenges in the context of global climate change concerns. Energy Policy 2004;32:801–10.
[73] Roos A, Rakos C. The limits of modelling. Experiences with bioenergy in practice – could models have predicted this outcome? Biomass Bioenergy 2000;18:331–40.
[74] Bindraban PS, Bulte EH, Conijn SG. Can large-scale biofuels production be sustainable by 2020? Agric Syst 2009;101:197–9.
[75] Yan J, Lin T. Biofuels in Asia. Appl Energy 2009;86:1–10.
[76] Gomiero T, Paoletti MG, Pimentel D. Biofuels: efficiency, ethics, and limits to human appropriation of ecosystem services. J Agric Environ Ethics 2010;23:403–34.
[77] Gerbens-Leenes P, Hoekstra A, Van Der Meer T. The water footprint of energy from biomass: a quantitative assessment and consequences of an increasing share of bio-energy in energy supply. Ecol Econ 2009;68:1052–60.
[78] Dominguez-Faus R, Powers SE, Burken JG, Alvarez PJ. The water footprint of biofuels: a drink or drive issue? Environ Sci Technol 2009;43:3005–10.
[79] Yang H, Zhou Y, Liu J. Land and water requirements of biofuel and implications for food supply and the environment in China. Energy Policy 2009;37:1876–85.
[80] Fitzherbert EB, Struebig MJ, Morel A, Danielsen F, Brühl CA, Donald PF, et al. How will oil palm expansion affect biodiversity. Trends Ecol Evol 2008;23:538–45.
[81] Kort J, Collins M, Ditsch D. A review of soil erosion potential associated with biomass crops. Biomass Bioenergy 1998;14:351–9.
[82] Dale VH, Kline KL, Wiens J, Fargione J. Biofuels: implications for land use and biodiversity. Washington, DC: Ecological Society of America (ESA); 2010.
[83] Plieninger T, Bens O. How the emergence of biofuels challenges environmental conservation. Environ Conserv 2008;34:273–5.
[84] Hennenberg KJ, Dragisic C, Haye S, Hewson J, Semroc B, Savy C, et al. The power of bioenergy-related standards to protect biodiversity. Conserv Biol 2010;24:412–23.
[85] Levy JB, Yoon E. Modeling global market entry decision by fuzzy logic with an application to country risk assessment. Eur J Oper Res 1995;82:53–78.
[86] Cornelissen A, Van Den Berg J, Koops W, Grossman M, Udo H. Assessment of the contribution of sustainability indicators to sustainable development: a novel approach using fuzzy set theory. Agric Ecosyst Environ 2001;86:173–85.
[87] Acosta-Michlik LA, Kumar KS, Klein RJ, Campe S. Application of fuzzy models to assess susceptibility to droughts from a socio-economic perspective. Reg Environ Change 2008;8:151–60.
[88] Eierdanz F, Alcamo J, Acosta-Michlik L, Krömker D, Tänzler D. Using fuzzy set theory to address the uncertainty of susceptibility to drought. Reg Environ Change 2008;8:197–205.
[89] Norman GR, Streiner DL. In: Norman GR, Streiner DL, Pdq Statistics, editors. Path analysis and structural equation modeling. third ed. Ontario: BC Decker; 2003. p. 218.
[90] Hanley N, Wright RE, Adamowicz V. Using choice experiments to value the environment. Environ Resour Econ 1998;11:413–28.
[91] Lee KC, Choi H, Lee DH, Kang S. Quantitative measurement of quality attribute preferences using conjoint analysis. In: Gilroy S, Harrison M, editors. Interactive systems: lecture notes in computer science, vol. 394. Berlin: Springer-Verlag; 2006. p. 213–24.
[92] Green PE, Srinivasan V. Conjoint analysis in marketing: new developments with implications for research and practice. J Mark 1990;54:3–19.
[93] Tano K, Kamuanga M, Faminow MD, Swallow B. Using conjoint analysis to estimate farmer's preferences for cattle traits in West Africa. Ecol Econ 2003;45:393–407.
[94] Stevens TH, White S, Kittredge DB, Dennis D. Factors affecting NIPF landowner participation in management programs: a Massachusetts case study. J For Econ 2002;184:169–84.
[95] Moran D, Mcvittie A, Allcroft DJ, Elston DA. Quantifying public preferences for agri-environmental policy in Scotland: a comparison of methods. Ecol Econ 2007;63:42–53.
[96] Blamey RK, Bennett JW, Louviere JJ, Morrison MD, Rolfe J. A test of policy labels in environmental choice modelling studies. Ecol Econ 2000;32:269–86.
[97] Hall C, McVittie A, Moran D. What does the public want from agriculture and the countryside? A review of evidence and methods. J Rural Stud 2004;20:211–25.
[98] Sayadi S, Gonzalez-Roa MC, Calatrava-Requena J. Public preferences for landscape features: the case of agricultural landscape in mountainous Mediterranean areas. Land Use Policy 2009;26:334–44.
[99] Orme BK. Which conjoint method should I use? Sequim: Sawtooth Software, Inc.; 2009.
[100] Bakker MM, Govers G, Kosmas C, Vanacker V, Van Oost K, Rounsevell M. Soil erosion as a driver of land-use change. Agric Ecosyst Environ 2005;105:467–81.
[101] Acosta-Michlik L, Rounsevell M, Bakker M, Doorn AV, Gómez Delgado M, Delgado M. An agent-based model to assess land use change in a traditional agricultural landscape of Portugal. J Land Use Sci 2010, reviewed and revised.
[102] Kleinbaum D, Kupper L, Muller K, Nizam A. Applied regression analysis and other multivariable methods. Brooks/Col, Belmont: Brooks/Cole Publishing Company; 1998.
[103] Roehrig SF. Probabilistic inference and path analysis. Decis Support Syst 1996;16:55–66.
[104] Stage FK, Carter HC, Nora A. Path analysis: an introduction and analysis of a decade of research. J Educ Res 2004;98:5–13.
[105] Van Acker V, Witlox F, Van Wee B. The effects of land use system on travel behavior: a structural equation modeling approach. Transp Plan Technol 2007;30:331–53.
[106] Srinivasa Setty KP, Natarajan R. Process analysis of becoming committed to energy conservation – a path analytic approach. Energy Convers Manage 1988;28:5–9.
[107] Alwin DF, Hauser RM. The decomposition effects in path analysis. Am Sociol Rev 1975;40:37–47.
[108] Acosta-Michlik L, Eierdanz F, Alcamo J, Krömker D, Galli F, Klein RJ, et al. An empirical application of the security diagram to assess the vulnerability of India to climatic stress. Die Erde 2006;137:223–52.

[109] Alcamo J, Acosta-Michlik L, Carius A, Eierdanz F, Klein R, Krömker D, et al. A new approach to quantifying and comparing vulnerability to drought. Reg Environ Change 2008;8:137–49.
[110] Sydorovych O, Wossink A. The meaning of agricultural sustainability: evidence from a conjoint choice survey. Agric Syst 2008;98:10–20.
[111] Mangoyana RB. Bioenergy for sustainable development: an African context. Phys Chem Earth 2009;34:59–64.
[112] Johnson FX, Matsika E. Bio-energy trade and regional development: the case of bio-ethanol in southern Africa. Energy Sustain Dev 2006;X: 42–53.